Landscape Effects on Stream Temperature in Minnesota Streams of the Lake Superior Basin

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Abstract

Changes in land use and land cover are known to be important factors causing thermal alterations in small streams. The heating of coldwater and coolwater streams influences aquatic communities that inhabit such environments. We recorded continuous stream temperature data at 50 sites during July - September of 2008 to better understand thermal controls on small streams (1st - 3rd order) within Minnesota's Lake Superior watershed, with specific interest in determining the role of water storage capacity and impervious surface cover. Local and landscape variables were used to predict in-stream temperature using multiple regression analyses. These analyses identify those variables most correlated with stream temperature, and therefore, most likely to influence thermal characteristics. Sites were selected to represent natural gradients of water storage capacity (0-86%) and impervious surface cover (0-26%) within each catchment. Stream habitat data were collected to explain natural temperature variation among sites due to local conditions. Results indicate that geomorphic (stream width and depth), atmospheric (air temperature), and local landscape (riparian shading) variables are all strongly correlated with stream temperature. Thermal characteristics are also influenced by regional landscape variables such as hydraulic conductivity and percent land cover classified as open water or emergent herbaceous wetlands. In contrast, neither impervious surface cover nor water storage capacity were good predictors of the stream temperature metrics summarized in this study. Land cover variables were selected more frequently in best-fit models when they were weighted by distance from the sampling

location, indicating that position in the watershed may be an important factor. These trends suggest that changes in land use and land cover have great potential to either mitigate or exacerbate the impacts on stream temperature from climate change, and stress the importance of effective land management.

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Introduction

Stream temperature is one of the most important indicators of stream health. Temperature is a major determinant of which aquatic communities can inhabit a stream, particularly for coldwater and coolwater systems (Gaffield et al. 2005; Web et al. 2008; Sahoo et al. 2009). Unfortunately, many of these systems are warming, in some cases nearing the upper tolerance limits for some of the most vulnerable species (Eaton and Scheller 1996; Wehrly et al. 2007; Stranko et al. 2008; Almodovar et al. 2012). Climate change and human-induced changes to the landscape are thought to be the dominant reasons for this warming trend (Stranko et al. 2008; Kaushal et al. 2010; Almodovar et al. 2012). As optimal thermal habitat diminishes, we can expect to see resulting declines in both range and population of temperature-sensitive fish and invertebrates (Hogg and Williams 1996; Wang and Kanehl 2003). Recent literature suggests these declines are already occurring, stressing the need for watershed management programs focused on maintaining thermal regimes (Stranko et al. 2008; Almodovar et al. 2012; Comte and Grenouillet 2013). For this to occur, we need a more comprehensive understanding of land-water interactions influencing water temperature.

Our goals with this study were to identify the primary factors controlling temperature in small, headwater streams, and to determine if landscape position within a watershed influences these relationships. Although many of these factors are well known (Poole and Berman 2001; Allan 2004; Caissie 2006; Webb et al. 2008), advances in mapping technologies are creating new ways to research spatial relationships at finer detail and over broader scales.

Controls on Stream Temperature

Researchers have studied relationships between climate and water temperature extensively during the last few decades (Brown 1969; Stefan and Preud'homme 1993; Webb et al. 2008). Correlations were observed as early as 1958 when Macan (1958) identified similarities between average air temperature and average stream temperature. Since then, advances in technology and statistical technique have led to countless publications reporting air-water temperature relationships with a high degree of explained variance (c.f., Stefan and Preud'homme 1993; Mohseni and Stefan 1999; Caissie et al. 2001; Webb et al. 2003). Air temperature alone, however, cannot explain the inconsistencies observed among streams in the same geographical location, nor can it account for differences longitudinally within any given stream. For that level of detail, additional variables must be considered. Previous research has identified four broad categories for the major controls on stream temperature: (1) geographic location, (2) atmospheric conditions, (3) landscape variables, and (4) geology / geomorphology (Caissie 2006; Wehrly et al. 2006; Hill et al. 2013).

Geographic Location

Geographic location can influence models predicting stream temperatures across a large geographic range (variation in latitude) or at drastically different elevations because it determines atmospheric conditions (Isaak and Hubert 2001; Caissie 2006). Issak and

Hubert (2001) and Danehy et al. (2005) found elevation to be an important variable predicting maximum stream temperatures in montane landscapes. It seems possible, however, that including air temperature as a model parameter may account for much of the variability existing between sites of different latitude and altitude, as suggested by the strong correlations observed between air and water temperatures at large geographic scales (Mohseni and Stefan 1999; Bogan et al. 2006). Of course, latitude and altitude would be especially important for regions where reliable air temperatures are not available (Hill et al. 2013).

Atmospheric Conditions

In many cases, atmospheric conditions are the strongest determinant of stream temperature. Heat exchange between the water surface and air, as well as between water and the streambed, drive thermal characteristics within streams. Heat exchange processes involve radiation, convection, conduction, evaporation, and advection (LeBlanc et al. 1997; Gaffield et al. 2005). One of the most important parameters is solar radiation, which results in both short-wave (direct solar energy as visible light) and long-wave (indirect solar energy emitted from objects as infrared light) radiation (LeBlanc et al. 1997; Johnson 2003). Additional variables include air temperature, relative humidity, atmospheric pressure, cloud cover, and wind speed, all of which interact to affect evaporation, conduction, and convection (Leblanc et al. 1997). Advection occurs when precipitation or any other water input to the stream has a measurable effect on temperature.

Landscape Variables

Interactions between streams and their surrounding landscape have been shown to greatly influence stream temperature as well (Johnson and Jones 2000; Pool and Berman 2001; Detenbeck et al. 2003). Riparian shading, which is negatively correlated with stream temperature, is an important mechanism through which humans can impact thermal conditions of streams (Brown 1969; Hetrick et al. 1998; Gaffield et al. 2005; Herb et al. 2009). Expanding urbanization not only displaces natural areas of vegetation that would provide shade, but also replaces forests and other pervious land cover types with roads, parking lots, and buildings that are impervious to groundwater infiltration. These changes to the landscape can have broad-scale impacts on ecosystem function within aquatic habitats (Allan 2004). There are multiple pathways through which urbanization causes thermal degradation (Paul and Meyer 2001). Vegetation removal along riparian zones of urban streams can immediately and significantly increase maximum stream temperatures by reducing riparian shading (Pluhowski 1970; Krause et al. 2004, Somers et al. 2013). Urbanization can also influence temperature by reducing groundwater infiltration. Increases in impervious surfaces prevent precipitation from seeping into the ground, resulting in a larger surface water to groundwater ratio (Brabec et al. 2002). Increases in warm surface water inputs and decreases in cold groundwater inputs degrade thermal habitat in streams, especially during summer months when stream temperatures are at a maximum and thermal refugia is at a minimum (Picard et al. 2003).

Reduced groundwater input results in lower baseflows and decreased stream depth (Klein 1979; LeBlanc et al. 1997), which further stresses streams. Again, this has its greatest effect during summer months when stream flows are already low (LeBlanc et al. 1997; Novotny and Stefan 2007). Because water has a high heat capacity, reductions in stream depth (and subsequent volume) result in more rapid temperature fluctuations, and potentially higher maximum temperatures (Krause et al. 2004). According to Herb et al. (2008) and Nelson and Palmer (2007), thermal pollution may be exacerbated by impervious surfaces during rain events if precipitation heats up as it flows across hot pavement before entering a stream. Although most storm events displayed little thermal impact, Herb et al. (2008) found that certain climatic conditions made thermal pollution more severe: (1) high atmospheric air and dew point temperatures, (2) short intense rainfall events on a hot sunny day, and (3) large percentages of the watershed comprised of paved surfaces. Lastly, researchers have observed higher ambient air temperatures near urban areas when compared to surrounding rural areas (Somers et al. 2013). This phenomenon is often termed the "urban heat island", and is thought to occur from conduction of heat from surfaces that absorb solar radiation during the day.

Discrepancy exists in the literature regarding the relationship between percent impervious surface cover (% ISC) and observable effects on stream ecosystems, although most indicate a threshold exists in the 5-15% ISC range (Paul and Meyer 2001). Some have found that temperature increases with increasing ISC (Galli 1990), while others report that a threshold ISC level exists before a response is observable (Klein 1979;

Wang et al. 2001). These inconsistencies may be explained by landscape structure. ISC located adjacent to a stream likely has greater influence on stream characteristics than the same ISC located some distance from the stream. Position in the watershed, or relative to the stream, has been observed to affect parameter influence on a measured response. Van Sickle and Johnson (2008) found that using distance-weighted proportions of landscape variables achieved better predictions of an index of biotic integrity for fish communities than using whole catchment proportions. The same may be true for any land cover type, or any response variable, for that matter. The scale at which these predictors should be measured is not currently well understood, but could be essential to identifying land-water interactions.

Geology / Geomorphology

The influence of geology and geomorphology on thermal regimes varies spatially and temporally. At large spatial scales, landscapes can be separated into basic geologic units resulting in similar geomorphic characteristics of streams within a given watershed. Based on different geologic settings, montane streams will have vastly different geomorphic characteristics (slope, flow velocity, groundwater input, streambed, etc.) than those in a glacial setting, which also have different characteristics than streams in karst topography (O'Driscoll and DeWalle 2006). Because of these differences, streams in different geologic settings have unique thermal characteristics. For example, high gradient streams have faster flow velocities; therefore, water travels farther downstream in a given amount of time than for low gradient streams. Since water temperature moves in the direction of equilibrium with air temperature, water gets warmer as it moves downstream. This results in high-gradient streams remaining cooler farther downstream than low-gradient streams (Wehrly et al. 2006). Geologic landscapes can also be quite diverse on small scales. Groundwater discharge, for example, can be variable both longitudinally and temporally within a stream (Wehrly et al. 2003; Lyons et al. 2010), which makes estimating this parameter very difficult. For this reason, few studies have included estimates for groundwater in predictive models. One recent study performed by Wehrly et al. (2006) successfully estimated potential groundwater input using surficial geology and local topography. Their method could be very useful if applicable to different regions / geologic settings. Additional geomorphic characteristics known to influence stream temperature include: stream gradient, width and depth, substrate composition, aspect, and entrenchment, each of which affects the amount of solar energy impinging on streams (Webb et al. 2008). Water temperature maxima diminish with steeper gradients, decreased width, and increased depth. Stream aspect, substrate composition, and degree of entrenchment are seldom included in predictive models; however, most researchers agree that these variables can affect thermal characteristics (Caissie 2006). For example, streams flowing east-west do not benefit from riparian shading as much as north-south flowing streams (Pluhowski 1970; LeBlanc et al. 1997). Also, entrenched streams with high vertical banks or those near elevated landforms are effectively shaded from the sun. The streambed may be more of a factor in wide shallow streams, especially if the substrate is dark and absorbs/conducts more heat energy (Brown 1969; Johnson 2004).

Collectively, this large body of literature provides a great deal of knowledge regarding temperature relationships; however, we still lack a complete understanding of landscape influences and the geographic scale at which they become important predictors of stream temperature. Additionally, little quantitative information exists to relate groundwater input to stream temperature. To address these issues, we gathered empirical data from fifty small streams (1st-3rd order) within Minnesota's Lake Superior basin during July-September of 2008. Our objectives were to:

(1) identify the most important predictor variables controlling stream temperature within the Lake Superior basin of Minnesota, USA;

(2) determine the role of composition versus structure in landscape control over temperature;

(3) assess the influence of surface water body types with respect to their influence on stream temperature;

(4) quantify how impervious surface cover interacts with water storage capacity to affect stream temperature.

We used multiple linear regression (MLR) analysis to identify the landscape variables most highly correlated with stream temperature dynamics in small, headwater streams of Minnesota's Lake Superior watershed. Additionally, we examined the role of landscape composition versus structure by comparing the influence of land cover variables at multiple scales: whole-catchment and distance-weighted percentages.

Methods

Geologic Setting

The study area included streams within the Lake Superior Basin of the Laurentian Great Lakes in Minnesota, USA (Figure 1). These streams are typically cool/coldwater systems that often support brook trout, brown trout, and rainbow trout in their lower reaches flowing into Lake Superior. The upper reaches of most catchments are dominated by forests and wetlands overlying unconsolidated glacial sediments that consist primarily of clay till mixed with outwash deposits. Bedrock underlying the glacial sediments consists of igneous units of the Duluth Complex and the North Shore Volcanics, exposed by uplift in the lower portion of the basin, adjacent to Lake Superior (Olcott et al. 1978, as cited in Detenbeck et al. 2003). The lower reaches of these catchments are dominated by forest cover, with fewer wetlands and some urban land use mainly along the shores of Lake Superior. Streams within Minnesota's Lake Superior basin are unique in that their steepest gradients are located in the lower sections near the mouth flowing into Lake Superior.

Site Selection

We identified a population of stream segments within Minnesota's Lake Superior basin using the ArcHydro extension of ESRI's ArcMap 9.3 (Maidment 2002). This software is designed to produce a network of streams within a watershed based on topographic information. The output layer from ArcHydro was compared to the Minnesota Department of Natural Resources 100k stream layer to ensure accuracy. Unconnected stream segments that arise in areas of topographic depressions were deleted from the output layer. This left us with a continuous network of streams (connected lines), each with a corresponding polygon to represent the subcatchment area for that particular stream section (Figure 2). We use the term *subcatchment* to describe an area of land draining directly to a specific stream segment. An aggregate area of all upstream subcatchments will be referred to as a *catchment*. To reduce confusion, we reserve the term *watershed* to describe the entire group of catchments that drain into Lake Superior.

We performed a stratified random selection of fifty independent sites (Figure 3) on first to third order streams with similar stream gradients, selected to span ranges of impervious surface cover and water storage capacity (Table 1). Study streams were limited to catchment areas less than 100 square kilometers to reduce temperature variability due to stream size. Additionally, sites were chosen within a radius of 60 km from Duluth, MN because of time constraints during data collection. Landscape variables other than impervious surface cover were summarized as catchment percentages using land cover data from the 2001 National Land Cover Database (NLCD) (Homer et al. 2004) (Figure 4). Impervious surface cover summaries were calculated from a data set created in 2000 by the Remote Sensing and Geospatial Analysis Laboratory at the University of Minnesota (Figure 5). Their lab used Landsat data to classify and map impervious surface area for the entire state of Minnesota as a continuous variable from 0 to 100 for each 30 m pixel (Bauer et al. 2002). We calculated percent coverage for five land cover categories: impervious surface cover (ISC), woody wetlands (WW), emergent herbaceous wetlands (EHW), open water (OW), and water storage capacity (WSC). The ISC percent cover was calculated by averaging percent imperviousness values for all 30 X 30 meter pixels located within each catchment. Land cover proportions for WW, EHW, and OW were calculated by summing the total area for each of these classifications within a catchment, and then dividing that sum by the total area of the catchment. We calculated WSC by summing percent cover for WW, EHW, and OW. Of the five land cover classes summarized in this study, WSC varied the most among sites (0-86%), followed by WW (0-78%), EHW (0-29%), ISC (0-26%) and OW (0-12%) (Table 2).

Distance Weighting

To determine if landscape position in the catchment affects relationships between land cover and stream temperature, we calculated inverse distance-weighted (IDW) values for each land cover category using methods described by Van Sickle and Johnson (2008) and King et al. (2005). We calculated IDW land cover proportions using the equation by King et al. (2005):

$$IDW_{prop} = \frac{\sum_k \left(I_k \cdot \frac{1}{flow\ length_k + 1} \right)}{\sum_k \left(\frac{1}{flow\ length_k + 1} \right)}$$

where "k" represents the specific land cover type. The function "I_k" is equal to 1 if pixel

k is classified as the specified land cover type and is equal to 0 for all other land cover categories. Flow length is the shortest flow path distance from the pixel to the sample site where the temperature logger is located. By calculating the inverse of flow length, we weighted land areas closer to the stream more heavily (having greater influence) than regions farther from the stream (Figure 6). Adding “1” to the flow length distance constrains all inverse flow length values between zero and one. This results in riparian land immediately adjacent to the site location having an influence of 1, but decreasing in influence with distance from the study site. "IDW_{prop}" represents the distance-weighted proportion of the catchment's land area comprised of a specific land cover type. The denominator normalizes IDW_{prop} to values between zero and one for a catchment of any size.

In addition to whole-catchment and distance weighted metrics, we also summarized land cover data within threshold distances of: 100 m, 200 m, 500 m, 1000 m, 2000 m, and 5000 m from the stream. Using ArcGIS, we created riparian buffers for each threshold distance that surrounded the stream network upstream of each site. We then calculated percent cover for each land cover type using the NLCD layer. Land cover polygons directly connected to the stream were also summarized and labeled "CON". Table A.1 contains a complete list of all land cover metrics.

Potential Groundwater Input

We estimated potential groundwater input using methods described by Baker et al. (2003). Digitized surficial geology and elevation data were used by Baker et al.

(2003) to model hydraulic potential in units of specific discharge. They applied these data to Darcy's Law, which states that groundwater flow is proportional to the product of hydraulic conductivity, hydraulic gradient, and the area of flow (Darcy 1856). We modified these methods slightly by solely using estimates of hydraulic conductivity as an indicator of groundwater potential. We felt this modification was valid because hydraulic conductivity comprised a much larger range of values (10^{-1} - 10^{-8} cm/s) than expected for hydraulic gradient (10^{-2} - 10^{-3}) within our study area (H. Mooers, UMD Department of Geological Sciences, personal communication), and is therefore the greatest determining factor of specific discharge. We used a digital surficial geology layer obtained from the Minnesota Department of Natural Resources to estimate hydraulic conductivity (Figure 7). Values were estimated based on expected average conductance for each geologic unit (Fetter 2000). Hydraulic conductivity estimates ranged from 0 to 86 meters per day, indicating a large difference in potential groundwater input among streams (Table 2).

Data Collection

Under-water temperature loggers (Optic StowAway® Temp Data logger, HOBO® Water Temperature Pro v2 Data Logger: model #U22-001) were placed at the downstream end of each selected catchment in the deepest and most shaded part of the stream. We fixed each temperature logger to rebar approximately six inches above the stream bed. These temperature loggers recorded in-stream temperature at five minute intervals during July, August, and September of 2008. Concurrently, we also recorded local air temperature at thirty minute intervals. Air temperature loggers (HOBO® Temp:

model #H08-001-02) were placed in clear waterproof cases and fixed to nearby trees for shading.

Local stream characteristics were measured within the stream reach upstream of the water temperature logger. Following Lyons (1992), we defined stream reach distance as 35 times the mean stream width. We limited reach distances to a minimum of 150 m, which is consistent with the standard operating procedures of the Minnesota Pollution Control Agency Biological Monitoring Program. This resulted in reach distances of 150 m to 268 m. We measured five characteristics at ten equidistant transects throughout the stream reach: stream width and depth, riparian shading, substrate size, and riparian land use. Substrate sizes and depth measurements were taken at four equidistant points, plus the thalweg, across the stream width at every transect. We used a convex spherical crown densiometer to estimate the percent of the stream that was shaded by riparian vegetation. Shading measurements were taken at six locations within each transect: (1,2) both wetted edges of the stream, as well as standing stream center facing (3) upstream, (4) downstream, (5) left bank, and (6) right bank. Table A.2 lists all data collected as well as methods of assessment. Variables involving multiple measurements per stream (e.g. width, depth, and shade) were averaged to produce one value for each site (Table A.3).

Data Summary and Analysis

Response variables were derived to reflect maximum, range, and variance metrics of water temperature at multiple time scales (Table 3). We chose maximum stream temperature during summer to reflect the time period of greatest stress for thermally sensitive stream biota (Webb et al. 2008; Arismendi et al. 2012). Range and variance metrics were chosen to indicate water temperature fluctuation, which can also stress stream biota (Wehrly et al. 2007; Stranko et al. 2008). Both maximum and range summaries were calculated as 1, 7 and 21 consecutive-day running averages. Daily and weekly temperature metrics are typical time period intervals summarized by previous temperature studies (Mohseni and Stefan 1999; Webb et al. 2003; Wehrly et al. 2007; Butryn et al. 2013). We chose 21 consecutive-day running averages as a way to express temperature averages over a longer time scale.

Data were initially analyzed by including all land cover variables (Table A.1) in an all-subsets multiple linear regression (AS-MLR). Resulting models commonly displayed strong multicollinearity because multiple summaries of the same land cover type would be selected in the same model (e.g. OWDW and OW2000). We reduced the number of explanatory variables and testing groups of variables independently. First, we removed variables containing a large number of values equal to zero, which included all "connected" and "threshold" land cover variables. Next, we created four groups of explanatory variables to test independently of one another. Each group differed by the method used to summarize land cover variables (Table 4). This grouping technique not only reduced multicollinearity, but it also allowed us to compare bulk catchment versus distance-weighted landscape variables, as well as differentiated versus undifferentiated surface water body classifications. All four groups also contained air temperature (AIR), riparian shading (SHADE), hydraulic conductivity (K), catchment area (AREA), stream depth (DEPTH), and stream width (WIDTH). We used a variance inflation factor to check for multicollinearity within each group of explanatory variables prior to testing the models. Then we performed an AS-MLR separately for each group using the Multi-Model Inference package (MuMIn) for the statistical software R. In total, 32 global models were tested: 4 groups of explanatory variables X 8 response variables. Where necessary, predictor variables were transformed using arcsine square root, log, and natural log transformations (Table 5). Models were evaluated based on second-order Akaike Information Criterion (AIC_c), adjusted R^2, and Mallow's Cp statistic. AIC_c was calculated as:

$$AICc = -2\ln\big(L(\theta|y)\big) + 2K\left(\frac{n}{n-K-1}\right)$$

where *ln(L(θ|y))* is the log likelihood function, *n* is the sample size, and *K* is the number of model parameters. We chose AIC_c instead of AIC because our sample size was small relative to the number of model parameters; Burnham and Anderson (2002) recommended the use of AIC_c when $n/K < 40$.

We calculated the relative importance of each explanatory variable for every AS-MLR analysis using the MuMIn package. Relative importance is defined as the sum of normalized model likelihoods for all models that include a variable of interest (Burnham and Anderson 2002). In other words, relative importance characterizes how frequently an explanatory variable is chosen in a set of models and how well those specific models fit the data. Explanatory variables with high relative importance are frequently selected in best-fit models, and most strongly influence the response variable. Since all-subsets regression evaluates all possible models, it is reasonable to assume that some of the models do not fit the data well and should therefore be excluded from analysis. It is unfortunately difficult to know where the exclusion cutoff should be made. For comparison purposes, we ranked resulting models by $AIC_{c,}$ and selected a group of top models with AIC_c values within 2 units of the overall best model (Delta $AIC_c < 2$), and a more inclusive second group with normalized model likelihoods collectively summing to 0.95 (95% confidence set). Figures 8, 10, and 12 display side-by-side comparisons of variable importance when estimated from top models (Delta $AIC_c < 2$) and from a larger pool of models (95% confidence set). These figures also provide comparisons of variable importance among the groups of explanatory variables listed in Table 4.

Lastly, we averaged parameter coefficients from the 95% confidence set and constructed 95% confidence intervals to determine consistency among models (Figures 9, 11, and 13).

Results

Maximum Stream Temperature

Summer water temperatures exhibited a wide range for all variables calculated (Table 3). Warmest maximum daily water temperatures ranged from 18.4°C to 29.3°C. Average 7 and 21 day maximum temperatures ranged between 16.9°C and 26.7°C. Although air temperature daily maxima (20.9 - 33.6°C) reached higher values than water temperature, site range variability was comparable (differences of 12.7°C and 10.9°C respectively). Best-fit models resulting from the AS-MLR analysis most frequently selected SHADE, AREA, K, AIR, and OWDW when predicting maximum daily stream temperatures (Figure 8). Correlation coefficients averaged from top models (95% confidence set) of an AS-MLR were (mean +/- 95% CI): SHADE (-3.15 +/- 1.79), AREA (0.91 +/- 0.59), K (-0.32 +/- 0.26), AIR (0.27 +/- 0.29), and OW (5.92 +/- 4.86) (Figure 9).

Stream Temperature Range

Maximum daily range in water temperature varied among sites from 3.9°C to 12.5°C (Table 3). Maximum daily range in air temperature varied among sites from 6.9°C to 27.3°C. SHADE, DEPTH, and WIDTH were selected most frequently in best-fit models predicting maximum stream temperature range (Figure 10). Correlation coefficients averaged from top models (95% confidence set) of an AS-MLR were (mean +/- 95% CI): SHADE (-2.71 +/- 1.83), DEPTH (-1.10 +/- 0.85), and WIDTH (1.28 +/- 1.18) (Figure 11).

Stream Temperature Variance

Stream temperature variance ranged among sites from 4.1°C to 16.4°C (Table 3). Air temperature variance ranged from 16.0°C to 49.5°C. Trends were more variable when predicting stream temperature variance; however, SHADE and DEPTH were selected most frequently in best-fit models (Figure 12). Correlation coefficients averaged from top models (95% confidence set) of an AS-MLR were (mean +/- 95% CI): SHADE

(-4.58 +/- 2.97) and DEPTH (-1.54 +/- 1.18) (Figure 13).

Distance Weighting

Land cover parameters at times displayed large differences between whole catchment and distance-weighted summaries (Table 2). Average differences between land coverage estimates were highest for impervious surface cover (10%) and lower for the other land cover classifications (WSC = 4%, WW = 3%, EHW = 1%, and OW = 0.5%). Not surprisingly, catchments having an abundance of a particular land cover type displayed greater disparity between whole catchment and distance-weighted percentages. The maximum change in percent cover when weighting land cover by distance from the site for ISC, WSC, WW, EHW, and OW was 53%, 22%, 19%, 11%, and 4% respectively (Figure 14). Although distance-weighted values of OW differed the least from bulk catchment percentages when compared to all land cover classes, OWDW displayed noticeable improvement in relative importance when predicting maximum stream temperatures (Figure 8). Similarly, EHWDW was selected more frequently than EHW in top models predicting stream temperature range. Water storage capacity was rarely selected in best-fit models. However, when wetlands were differentiated, open water and emergent herbaceous wetlands became important predictors (Figures 8 and 10).

ISC X WSC

Regression analysis indicated a lack of significance ($p = 0.89$; $n = 50$) for an interaction term between ISC and WSC in the model: WT-H-21-Max = ISC + WSC + ISC·WSC. Similar models predicting temperature range and variance also indicated a lack of significance for ISC·WSC ($p = 0.85$ and $p = 0.91$; $n = 50$).

Top Statistical Models

Regression analyses identified three top models to characterize landscape interactions with stream temperature dynamics. The best-fit model (based on adjusted R^2, AIC_c, and Mallow's C_p statistic) for maximum daily stream temperature was:

$$WT\text{-}H\text{-}21\text{-}Max = 13.15 + (0.24 \cdot AIR) + (5.32 \cdot OWDW) - (0.30 \cdot K) - (2.77 \cdot SHADE) + (0.93 \cdot AREA)$$

where the response variable "*WT-H-21-Max"* = the warmest maximum water temperature averaged over 21 consecutive days, "*AIR"* = maximum air temperature averaged over the same 21 day period, "*OWDW"* = percent land cover characterized as open water and inversely weighted by distance from the temperature logger, *"K"* = hydraulic conductivity, *"SHADE"* = riparian shading, and *"AREA"* = catchment area. This model explained 62% of variation in the data ($p < 0.0001$) (Table 6).

The best-fit model for stream temperature range was:

$$WT\text{-}H\text{-}21\text{-}RANGE = 7.42 + (0.01 \cdot AIR) - (2.34 \cdot SHADE) - (1.21 \cdot DEPTH) + (1.49 \cdot WIDTH) + (2.96 \cdot EHWDW)$$

where the response variable *"WT-H-21-RANGE"* = the maximum daily range in water temperature averaged over 21 consecutive days, *"AIR"* = the maximum daily range in air temperature averaged over the same 21 day period, *"SHADE"* = riparian shading, *"DEPTH"* = mean stream depth, *"WIDTH"* = mean stream width, and *"EHWDW"* = percent land cover characterized as emergent herbaceous wetlands and inversely weighted by distance from the temperature logger. This model explained 30% of variation in the data ($p < 0.001$) (Table 6).

The best-fit model for stream temperature variance was:

$$WT\text{-}VARIANCE = 7.66 + (0.12 \cdot AIR) - (3.42 \cdot SHADE) - (1.05 \cdot DEPTH) + (1.45 \cdot AREA)$$

where the response variable *"WT-VARIANCE"* = the water temperature variance during July through September of 2008, *"AIR"* = the air temperature variance during the same time period, *"SHADE"* = riparian shading, *"DEPTH"* = mean stream depth, and *"AREA"* = catchment area. This model explained 62% of variation in the data ($p < 0.0001$) (Table 6).

Discussion

Important Predictors of Stream Temperature

Our results suggest that summer daily maximum stream temperatures in the Lake Superior basin of Minnesota are influenced primarily by air temperature, riparian shading, catchment size, hydraulic conductivity of the surficial geology, and proportion open water within watersheds. The strongest of these relationships was riparian shading, which reduces stream temperatures by blocking solar radiation to the stream (Brown 1969; Rutherford et al. 1997). Also negatively correlated to water temperature was hydraulic conductivity, which is a measure of potential groundwater contribution and can reduce maximum stream temperatures through advection (Wehrly et al. 2006). Conversely, air temperature, catchment size, and open water proportions display positive correlations with maximum stream temperatures. Catchment size and percent coverage of open water increase stream temperatures by increasing the duration of exposure to atmospheric conditions and the amount of heat energy added to the system (Stefan and Preud'homme 1993; Poole and Berman 2001; Webb et al. 2003).

Surprisingly, air temperature was included less frequently in models predicting maximum stream temperatures during the warmest 7 and 21 consecutive-day time periods (Figure 8). It was, however, included in more than 90% of models predicting maximum stream temperature during the warmest day of the summer (Figure 8). In contrast, Pilgrim et al. (1998) suggested that short time intervals had poor correlations because weather parameters other than air temperature (e.g. wind and cloud cover) can affect the correlation. The difference exists in the type of response variable being analyzed. Pilgrim et al. (1998) predicted weekly maximum temperatures (many observations per site), whereas we predicted the maximum 1-day stream temperature (one observation per site). Sampling multiple observations over time at each site averages out some of the variance caused by weather parameters such as clouds or wind. This is likely the reason our 1-day metrics display a stronger air-water temperature correlation, because they are less likely to experience variable weather conditions than the 7-day or 21-day running averages.

Not all temperature response variables were influenced by the same landscape variables. Hydraulic conductivity, for example, was negatively correlated with maximum stream temperatures, but did not strongly influence temperature fluctuation metrics (Figures 8, 10, and 12). We believe this trend can be explained by the temperature difference between surface water and local groundwater sources. During summer, minimum stream temperatures were warmer than groundwater inflow (H. Mooers, UMD Department of Geological Sciences, personal communication). Although groundwater input does, in fact, lower maximum stream temperatures, it also lowers minimum stream temperatures, potentially negating any influence on temperature fluctuation. Groundwater input would, however, likely buffer stream temperature during the spring or fall when: 1) groundwater temperature is between the maximum and minimum surface water temperature, and 2) groundwater recharge (and subsequent input to streams) is greater.

Morphological characteristics such as stream width and depth appeared to influence temperature fluctuation (variance and range) but had little effect on maximum temperatures (Figures 8, 10, and 12). This does not necessarily suggest that stream morphology is not important for stream temperature maxima. Rather, a more likely explanation is that catchment area may explain some of the variance in stream temperature that stream width would explain. Although we made every effort to minimize collinearity by restricting stream size and grouping explanatory variables, some ecological variables are naturally collinear. Since streams with larger catchments tend to be wider, catchment area indirectly influences stream temperature by having greater surface area, thus increasing solar radiation and heat flux between air and water. This correlation would not be true for streams arising from lake or wetland sources. However, given that only 4% of our sites contained upstream open water sources within a 500 meter riparian buffer, our population of streams most likely follows this trend. Wehrly et al. (2006) also found that catchment area had a strong influence on stream temperature maxima, and concluded that longitudinal position within a stream controls the amount of exposure water has with the atmosphere. During warm summer months, cool headwater streams warm with time and distance traveled above ground, assuming larger surface water to groundwater ratios as water travels downstream. This further supports the observed correlation between catchment area and maximum stream temperature. Another possible explanation is that width may have a larger influence in broad rivers where shade from riparian vegetation does not reach the stream center. However, the largest mean width in this study was only 6.9 meters, indicating that these streams were narrow relative to average tree height, allowing shade to exert a larger relative effect.

Our best-fit model predicting maximum stream temperature range had a lower proportion of explained variance (adj. R^2 = 0.30) than models predicting stream temperature maxima and variance (adj. R^2 = 0.62) (Table 6), indicating that additional environmental factors contributing to water temperature range should be considered.

This project was intended to identify the landscape variables most strongly correlated with stream temperature, and to determine how spatial scale affects these relationships. It was not intended to create statistical models that predict stream temperature. However, it may still be beneficial to compare our best model with other temperature models reported in the literature. Our best-fit model explained 62% (adjusted R^2) of the variance in streams with regard to maximum daily temperatures averaged over the warmest 21 consecutive-day period during summer months (Table 6). This model was remarkably similar (in selected parameters and explained variance) to models reported by Wehrly et al. (2006) that predicted mean July water temperature in lower Michigan streams. They reported adjusted R^2 values of 63% and 65% when including similar variables such as air temperature (β = +0.466), local groundwater (β = -0.810), catchment area (β = +1.728), local forest (β = -1.463), and percent lakes and wetlands (β = +1.644). Such agreement lends support for the accuracy of these relationships, and suggests that these models can be applied to other regions with similar geologic settings.

Landscape Position

The effects of watershed position and spatial scale are also important to consider for many questions important to stream ecologists (Allan and Johnson 1997; Kratz et al. 1997; Wehrly et al. 2006). We included inverse distance weighted estimates for land cover classifications in our regression analysis to examine the effect of watershed position, and to test if spatial scale matters when quantifying land use / land cover. We found an increase in relative importance for some distance weighted land cover proportions over bulk catchment summaries, but not all. Open water was not considered an important variable when predicting stream temperature maxima until it was weighted by distance from the stream. Once distance weighted, open water was selected in every model within two AICc values of the overall best model (Delta $AIC_c < 2$). Similarly, EHWDW was more important than EHW in models predicting stream temperature range. These trends suggest both OW and EHW have greater influence on stream temperature when located closer to the stream, and that these distance weighted metrics are better predictors of stream temperature dynamics than bulk catchment summaries.

Surface Water Storage

Additionally, we explored the importance of differentiating surface water body types into multiple land cover classifications (OW, EHW, and WW). Lumping together all surface water body types into one explanatory variable (WSC) ignores functional differences as related to temperature. Results from AS-MLR analyses indicated that, overall, WSC was not an important predictor of stream temperature. By differentiating lakes and wetland types, we learned that higher fractions of OW and EHW were correlated with increased stream temperature maxima and range, but WW either were not correlated or had only a small negative correlation with temperature maxima and range (Figures 9 and 11). This helps to explain why WSC was not an important predictor of stream temperature, and suggests that differentiated surface water classes are better summaries to use than WSC. Overall, these results agree with recent literature (Wiley et al. 1997; Wang et al. 2001; Brazner et al. 2007) suggesting that both landscape structure and composition are important considerations with regard to landscape influence on stream temperature.

Impervious Surface Cover

ISC was not selected as an important predictor for any of the stream temperature metrics we tested. A lack of correlation may be explained by the scale at which we measured the temperature response. One mechanism by which ISC can increase stream temperature is through the warming of surface runoff as it flows over hot surfaces, such as asphalt. Herb et al. (2008) found that storm events often had little thermal impact on streams; however, a few storms each year exerted a large thermal effect due to the characteristics of the rainfall event and the pre-storm weather conditions. The largest temperature changes were produced from short duration events (< 2 hours). Similarly, Nelson and Palmer (2008) reported average temperature surges of 2-8 hours in duration. The shortest time scale we summarized for temperature response was 1 day, suggesting that our data are at too broad a temporal scale to observe temperature surges from storm events.

ISC often replaces natural vegetation, thus reducing groundwater infiltration and increasing surface runoff (LeBlanc et al. 1997; Brabec et al. 2002; Kinouchi et al. 2007). Given enough ISC, changes to the timing and volume of storm water delivered to the stream can occur. Resulting hydrologic changes include: larger surface-to-groundwater ratios, flashier storm events, larger floods, increased erosion, and decreased mid-summer baseflows (Paul and Meyer 2001). Reduced groundwater input during mid-to-late summer could cause increased maximum water temperature, which in turn can deplete suitable thermal habitat for temperature-sensitive fish (Galli 1990). We did not observe an increase in maximum stream temperature with ISC, suggesting we either did not sample large enough densities of ISC (0-26.1%), or there is no relationship between ISC and stream temperature for the sampled data set. For comparison, other researchers report threshold values of ISC causing thermal degradation well below our maximum observation - 12% and 11% reported by Galli (1990) and Wang et al. (2003) respectively.

Summary

This project identified the landscape variables most strongly correlated with stream temperature, and investigated how spatial scale affects these relationships for streams in Minnesota's Lake Superior drainage. Our analysis characterized land-stream interactions at an entire watershed scale, which is a common responsibility for land managers and makes our results more applicable to them. We found that landscape variables are strong controllers of temperature dynamics, which emphasizes the importance of effective land management.

Both open water and emergent herbaceous wetlands can increase maximum stream temperature through advection, potentially limiting suitable thermal habitat for temperature-sensitive fish. Additionally, results suggest that landscape influence varies with spatial scale. In other words, land use and land cover have a greater effect on stream temperature when in close proximity to the stream. Managers can use this information to identify streams with suitable thermal habitat, as well as those streams at greatest risk for thermal degradation. Also, this knowledge allows funds to be allocated more effectively to protect thermal refugia. For instance, we should rethink how we deal with stormwater within urban environments. While retention ponds benefit streams by removing pollutants from runoff and lowering peak discharges to streams, they may act as heat sources by absorbing solar radiation. Increasing vegetation surrounding these ponds, or any open water source, would provide shade and limit temperature spikes during hot, sunny days. Alternatively, underground stormwater storage systems may be a more effective method of reducing heat input to streams from stormwater. Increased use of rain gardens and other best management practices designed to reduce surface runoff would add to the solution.

Though the effects of shading have been well-documented in temperature studies (Brown 1969; Rutherford et al. 1997; Herb et al. 2009), our findings reinforce the importance of protecting riparian buffer zones of vegetation, particularly for small, headwater streams. Our results indicate that riparian shading is the most important variable we can manipulate to affect stream temperature, which agrees with the findings of Herb et al. (2009). This should be an important consideration for future land development projects located near coldwater streams.

As human populations continue to grow, urbanization and development of impervious surfaces displace natural areas of vegetation. Previous research suggests this trend will likely decrease shading and groundwater infiltration, which could lead to warmer streams with increased temperature fluctuation (Galli 1990; Gaffield et al. 2005). Although we did not observe strong correlations between ISC and water temperature, a relationship clearly exists at least in highly urbanized environments. Most research linking urbanization with increased water temperature either studied higher concentrations of ISC (Pluhowski 1970), or analyzed temperature metrics as they changed over short time periods (Galli 1990; Roa-Espinosa et al. 2003; Herb et al. 2008). Since our temperature response was limited to one point in time and was measured at the scale of 1 day or longer, any relationship with ISC was likely lost in the averages. Future development should include mitigation techniques designed to reduce surface runoff, increase groundwater infiltration, and maintain riparian buffers of at least 30 meters (Galli 1990; Townsend et al. 2003; DeWalle 2010).

Groundwater input has been mentioned repeatedly in the literature as an important predictor of stream temperature (Johnson 2004; Danehy et al. 2005; O'Driscoll and DeWalle 2006). However, few studies have estimated groundwater potential at the watershed scale (Wehrly et al. 2006). We used surficial geology to estimate potential groundwater input, and confirmed that it has a strong negative correlation with maximum water temperature. This method of estimating potential groundwater input, modified from Baker et al. (2003), has broad-scale implications for ecological management, watershed planning, and general stream research. It can be applied by fisheries managers looking for streams that have the greatest ability to resist increasing temperatures projected from current climate change scenarios (Pilgrim et al. 1998; Nelson et al. 2009; Lyons et al. 2010; Wenger et al. 2011). Groundwater-fed streams containing thermal refugia can then be protected through planning and resource allocation.

This study suggests future changes in land use and land cover have great potential to influence stream temperature dynamics and resulting fish distribution. Higher resolution landscape data and multi-year, high frequency temperature data are needed to increase our understanding of land-water interactions, which is essential if we hope to maintain adequate thermal habitat for coldwater fishes in the face of continued urban development and current climate change projections.

Tables

TABLE 1.—Distribution of sites with respect to impervious surface cover and water storage capacity gradients. Sites were selected to represent the natural ranges for both of these landscape variables across the study area. Water storage capacity was calculated as the percent area sum of open water + woody wetlands + emergent herbaceous wetlands within each catchment. Very few catchments contained high densities for both impervious surfaces and water storage.

Impervious Surface Cover (% of catchment)	Water Storage Capacity (% of catchment)				
	0 - 5%	5 - 10%	10 - 20%	> 20%	Totals
0 - 2.5%	8	7	4	8	27
2.5 - 5%	4	3	0	1	8
5 - 10%	1	1	2	2	6
> 10%	5	2	2	0	9

TABLE 2.—Catchment and reach characteristics for 50 sites within Minnesota's Lake Superior watershed. Percentages for land cover classifications were calculated from the 2001 National Land Cover Database and the Minnesota Statewide Impervious Surface Area data set (2000, University of MN). Hydraulic conductivity was estimated from the Department of Natural Resources surficial geology data set. Stream reach characteristics were measured in the summer of 2008; see Table A.2 for methods.

Abbreviation	Variable description (units)	Min	Max	Mean	SD
Area	Catchment area (km^2)	1.4	91.4	21.8	16.8
K	Hydraulic conductivity (m/day)	0.0	86.4	0.1	49.9
ISC	Impervious surface cover (%)	0.1	26.1	4.8	6.1
ISCDW	Impervious surface cover, distance weighted (%)	0.0	71.4	14.3	18.0
WW	Woody wetlands (%)	0.0	78.0	10.4	16.9
WWDW	Woody wetlands, distance weighted (%)	0.0	62.0	8.1	12.4
EHW	Emergent herbaceous wetlands (%)	0.0	28.8	3.4	5.0
EHWDW	Emergent herbaceous wetlands, distance weighted (%)	0.0	39.0	4.3	6.8
OW	Open water (%)	0.0	11.8	1.5	2.7
OWDW	Open water, distance weighted (%)	0.0	11.5	1.2	2.5
WSC	Water storage capacity (%)	0.5	86.2	15.2	20.3
WSCDW	Water storage capacity, distance weighted (%)	0.2	69.1	13.6	16.5
Shade	Riparian shading (%)	16.1	96.9	65.4	24.1
Width	Mean stream width (m)	1.3	7.7	3.2	1.4
Depth	Mean stream depth (m)	0.06	1.0	0.3	0.2

TABLE 3.—Water and air temperature characteristics for 50 sites within Minnesota's Lake Superior watershed. Data were summarized from continuous water (5 minute interval) and air (30 minute interval) temperature monitoring during July-September of 2008. Water temperature loggers were fixed to rebar and placed in the deepest part of the reach with the greatest amount of shade. Air temperature loggers were placed in shaded areas and fixed to streamside woody vegetation.

Abbreviation	Variable description (units)	Min	Max	Mean	SD
WT-H-1-Max	Warmest maximum water temperature (°C)	18.4	29.3	23.6	2.3
WT-H-7-Max	Warmest maximum water temperature - 7 consecutive day average (°C)	17.5	26.7	21.5	2.0
WT-H-21-Max	Warmest maximum water temperature - 21 consecutive day average (°C)	16.9	26.1	20.6	2.0
WT-H-1-Range	Maximum daily range in water temperature (°C)	3.9	12.5	7.1	1.9
WT-H-7-Range	Maximum daily range in water temperature - 7 consecutive day average (°C)	2.8	10.4	5.3	1.6
WT-H-21-Range	Maximum daily range in water temperature - 21 consecutive day average (°C)	2.2	9.7	4.5	1.5
WT-H-1-Variance	Maximum daily variance in water temperature (°C)	1.4	19.8	6.7	4.2
WT-Variance	Summer water temperature variance $(°C)^2$	4.1	16.4	8.7	2.8
AT-H-1-Max	Warmest maximum air temperature (°C)	20.9	33.6	28.4	2.8
AT-H-7-Max	Warmest maximum air temperature - 7 consecutive day average (°C)	21.9	28.4	25.4	1.4
AT-H-21-Max	Warmest maximum air temperature - 21 consecutive day average (°C)	20.4	27.0	24.2	1.5
AT-H-1-Range	Maximum daily range in air temperature (°C)	6.9	27.3	18.0	5.3
AT-H-7-Range	Maximum daily range in air temperature - 7 consecutive day average (°C)	8.5	19.4	14.7	2.3
AT-H-21-Range	Maximum daily range in air temperature - 21 consecutive day average (°C)	9.0	18.3	13.5	2.4
AT-H-1-Variance	Maximum daily variance in air temperature (°C)	3.5	91.8	45.9	20.7
AT-Variance	Summer air temperature variance $(°C)^2$	16.0	49.5	32.3	8.2

TABLE 4.—Groups of explanatory variables tested independently using all-subsets multiple linear regression. We used a variance inflation factor (VIF < 3) to check for multicollinearity within each group of explanatory variables prior to testing the models. See Table 2 for variable descriptions.

Group	Name	Explanatory Variables
1	Bulk	AIR, SHADE, K, AREA, DEPTH, WIDTH, ISC, WW, EHW, OW
2	Bulk-WSC	AIR, SHADE, K, AREA, DEPTH, WIDTH, ISC, WSC
3	DW	AIR, SHADE, K, AREA, DEPTH, WIDTH, ISCDW, WWDW, EHWDW, OWDW
4	DW-WSC	AIR, SHADE, K, AREA, DEPTH, WIDTH, ISCDW, WSCDW

TABLE 5.—Transformations applied to explanatory variables prior to regression analyses.

Variable	Transformation
All land cover variables	arcsine square root
Riparian shading	arcsine square root
Hydraulic conductivity	log
Catchment area	ln
Stream width	ln
Stream depth	ln

TABLE 6.—Descriptive statistics for the best models selected from all-subsets multiple linear regression analyses. Selection criteria included Akaike Information Criterion (AIC_c), adjusted R^2, and Mallow's C_p statistic. Statistical analyses we conducted using the Multi-Model Inference package (MuMIn) for the statistical software R.

	WT-H-21-Max		WT-H-21-Range		WT-Summer-Variance	
Model Parameters	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|
Intercept	13.15	0.0008	7.42	0.0012	7.66	0.0093
Air temperature	0.24	0.0777	0.09	0.2681	0.12	0.0045
Riparian shading	-2.77	0.0009	-2.34	0.0081	-3.42	0.0079
Catchment area	0.93	0.0006			1.45	0.0002
Hydraulic conductivity	-0.30	0.0134				
Open water (distance weighted)	5.32	0.0268				
Emergent herbaceous wetlands (distance weighted)			2.96	0.0738		
Mean stream width			1.49	0.0038		
Mean stream depth			-1.21	0.0019	-1.05	0.0239

Model Diagnostics	WT-H-21-Max	WT-H-21-Range	WT-Summer-Variance
Adjusted R^2	0.62	0.30	0.62
Pr > F	< 0.0001	< 0.001	< 0.0001
AIC_c	174	171	205
Mallow's Cp	14.7	5.6	10.7

Figure Captions

FIGURE 1.—Map of study area showing Minnesota's Lake Superior watershed. The drainage basin was delineated from a statewide 30m digital elevation model using the ArcHydro extension of ESRI's ArcMap 9.3.

FIGURE 2.—(A) Lake Superior watershed displaying the final output of ArcHydro, which was a stream network connected by nodes at each confluence. (B) A closer view of the Lester/Amity catchment shows subcatchment polygons delineated for each line segment.

FIGURE 3.—Site map displaying 50 randomly selected sampling locations and their catchments within Minnesota's Lake Superior basin. Selection was restricted to first-third order streams above the escarpment to keep stream sizes and gradients relatively similar among sites.

FIGURE 4.—Dominant land cover classifications mapped within Minnesota's Lake Superior watershed from the 2001 National Land Cover Database. Percent cover within each catchment was calculated for open water, woody wetlands, and emergent herbaceous wetlands.

FIGURE 5.—Impervious surface area mapped for the entire state of Minnesota (only NE MN shown) at a 30 m pixel resolution. This data layer was created using Landsat

imagery for the 2000 time period by the Remote Sensing and Geospatial Analysis Laboratory at the University of Minnesota. Impervious surface area was classified as a continuous variable from 0 to 100 for each 30 m pixel. We calculated percent impervious surface cover by averaging percent imperviousness values for all pixels located within each catchment.

FIGURE 6.— Map of Amity Creek catchment showing estimated flow path distance from the stream sampling site. Flow path distance was used to calculate inverse distance-weighted land cover summaries.

FIGURE 7.—Hydraulic conductivity map of Minnesota's Lake Superior basin, estimated from the MN Department of Natural Resources surficial geology data set. We used ESRI's ArcMap 9.3 to assign hydraulic conductivity estimates to each surficial geology class based on published ranges (Fetter 2000). Hydraulic conductivity values were summarized as mean conductance for each site catchment and used as a proxy of potential groundwater input to predict stream temperature.

FIGURE 8.—Relative importance of explanatory variables when predicting **(A)** the warmest maximum stream temperature and maximum daily stream temperature averaged over **(B)** 7 and **(C)** 21 consecutive days during July-September of 2008. Relative importance is the sum of normalized model likelihoods for all models (from an all-

subsets regression) that include the explanatory variable of interest. Explanatory variables selected frequently in best-fit models (model selection based on AIC_c) have high variable importance. Here, we show variable importance summarized for **(Left)** a more inclusive set of models (95% confidence set) and **(Right)** a smaller set of models having AIC_c values within two units of the best model (Delta $AIC_c < 2.0$). See Table 4 for explanatory variable groupings (colors) and Table 2 for catchment and reach characteristics (x-axis).

FIGURE 9.— Parameter coefficients (points) averaged from resulting models of an all-subsets multiple linear regression predicting maximum daily stream temperature (WT-H-21-Max). Here, we show comparisons between **(Left)** Bulk and **(Right)** DW explanatory variables. See Table 4 for an explanation of Bulk and DW explanatory variable groups. Horizontal lines represent 95% confidence intervals set around model-averaged estimates. Asterisks denote significance of model-averaged coefficients ($\beta \neq 0$, $\alpha = 0.05$).

FIGURE 10.—Relative importance of explanatory variables when predicting **(A)** maximum daily stream temperature range and maximum daily stream temperature range averaged over **(B)** 7 and **(C)** 21 consecutive days during July-September of 2008. Relative importance is the sum of normalized model likelihoods for all models that include the explanatory variable of interest. Here, we show variable importance summarized for **(Left)** a more inclusive set of models (95% confidence set) and **(Right)** a

smaller set of models having AIC_c values within two units of the best model (Delta AIC_c < 2.0). See Table 4 for explanatory variable groupings (colors) and Table 2 for catchment and reach characteristics (x-axis).

FIGURE 11.—Parameter coefficients (points) averaged from resulting models of an all-subsets multiple linear regression predicting maximum daily range in stream temperature (WT-H-21-Range). Here, we show comparisons between **(Left)** Bulk and **(Right)** DW explanatory variables. See Table 4 for an explanation of Bulk and DW explanatory variable groups. Horizontal lines represent 95% confidence intervals set around model-averaged estimates. Asterisks denote significance of model-averaged coefficients ($\beta \neq 0$, $\alpha = 0.05$).

FIGURE 12.—Relative importance of explanatory variables when predicting **(A)** maximum daily stream temperature variance and **(B)** summer-long stream temperature variance during July-September of 2008. Relative importance is the sum of normalized model likelihoods for all models that include the explanatory variable of interest. Here, we show variable importance summarized for **(Left)** a more inclusive set of models (95% confidence set) and **(Right)** a smaller set of models having AIC_c values within two units of the best model (Delta AIC_c < 2.0). See Table 4 for explanatory variable groupings (colors) and Table 2 for catchment and reach characteristics (x-axis).

FIGURE 13.—Parameter coefficients (points) averaged from resulting models of an all-subsets multiple linear regression predicting stream temperature variance. Here, we show comparisons between **(Left)** Bulk and **(Right)** DW explanatory variables. See Table 4 for an explanation of Bulk and DW explanatory variable groups. Horizontal lines represent 95% confidence intervals set around model-averaged estimates. Asterisks denote significance of model-averaged coefficients ($\beta \neq 0$, $\alpha = 0.05$).

FIGURE 14.— Changes in percent land coverage when **(A)** impervious surface, **(B)** open water, **(C)** woody wetlands, and **(D)** emergent herbaceous wetlands were weighted by inverse-distance from the stream sampling location. Site catchments (x-axis) were listed in order of increasing gain in percent coverage.

FIGURE 15.—Historical climate data for Duluth, Minnesota. Average maximum air temperature (left axis) and total precipitation (right axis) were for summarized for July-August, annually from 1984-2013. Data were obtained from the Duluth International Airport weather station (COOP ID 212248). For comparison, our sampling year (2008) is highlighted with a red circle.

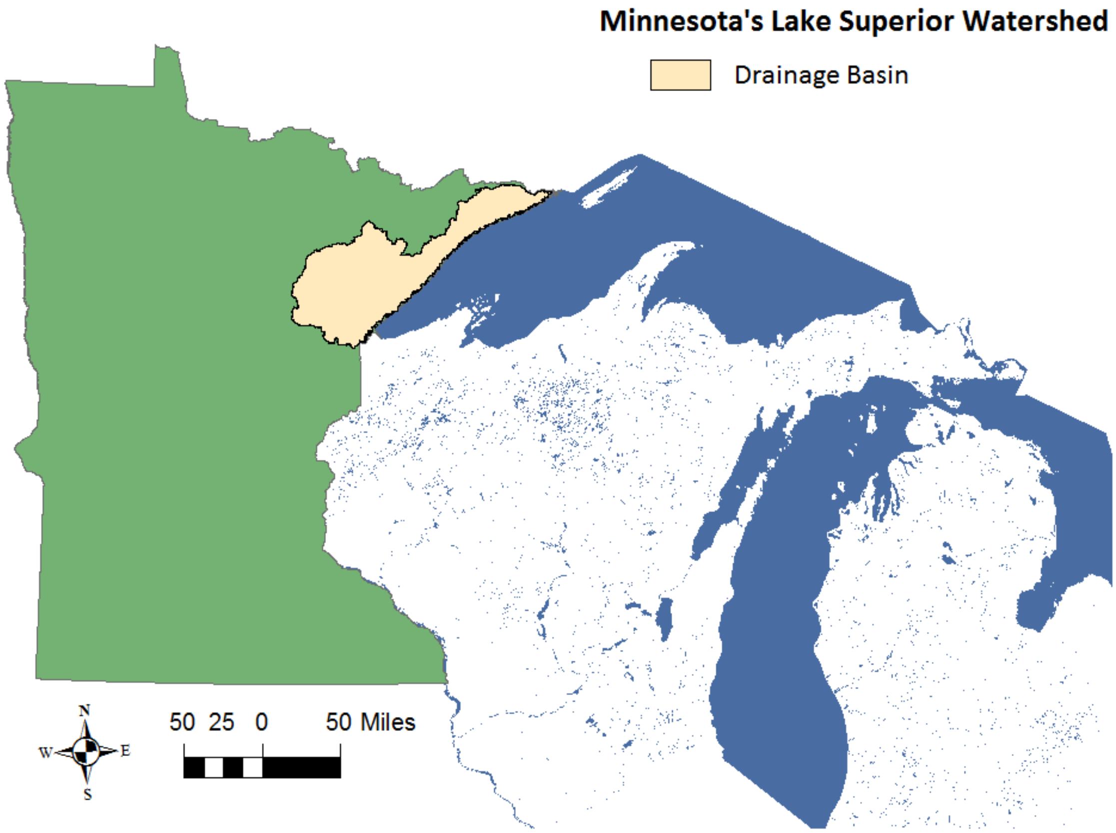

Minnesota's Lake Superior Watershed
Drainage Basin
N
W
E
S
50 25 0 50 Miles

FIGURE 1.

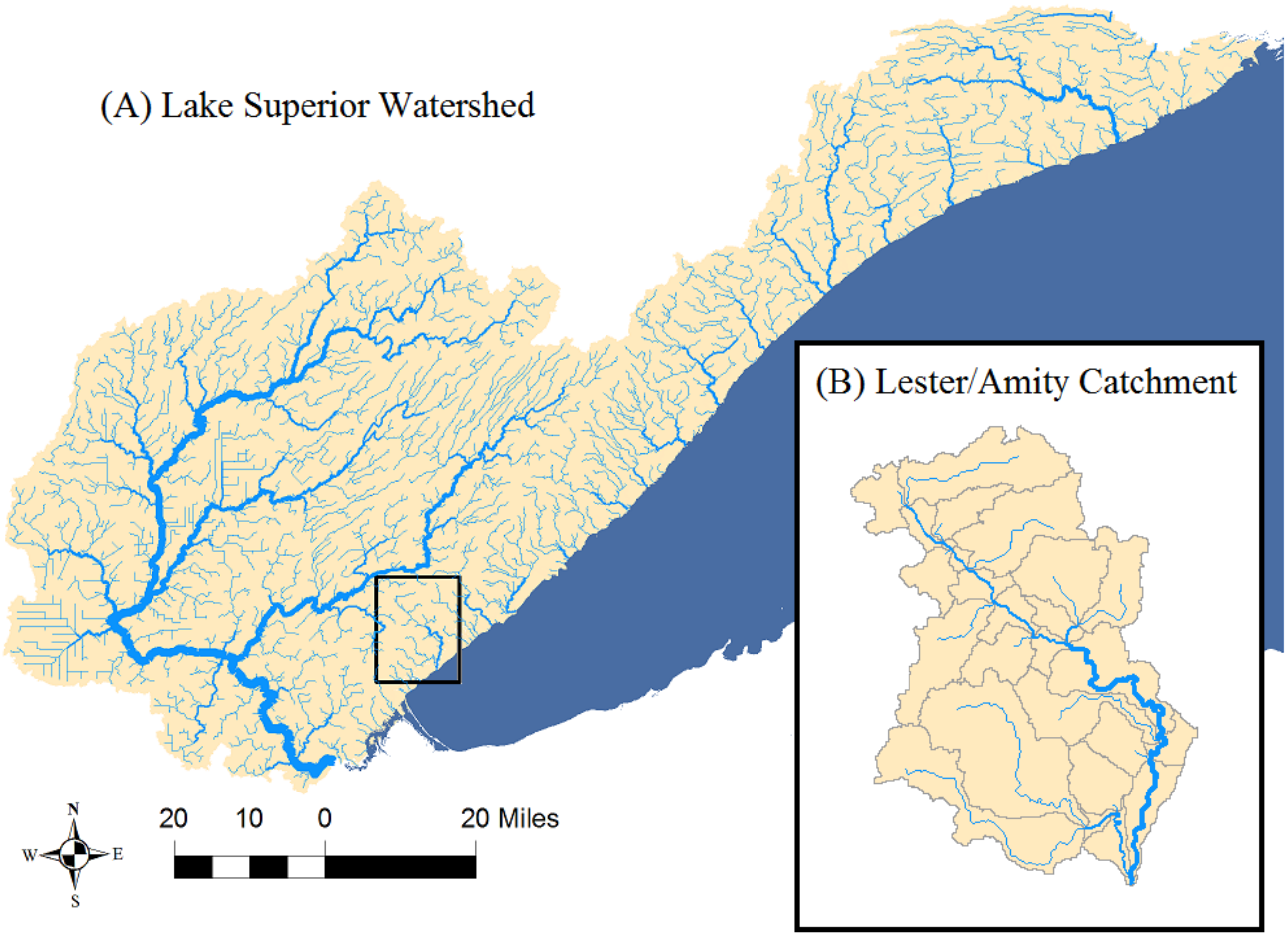

(A) Lake Superior Watershed
(B) Lester/Amity Catchment
N
W
E
S
20 10 0 20 Miles

FIGURE 2.

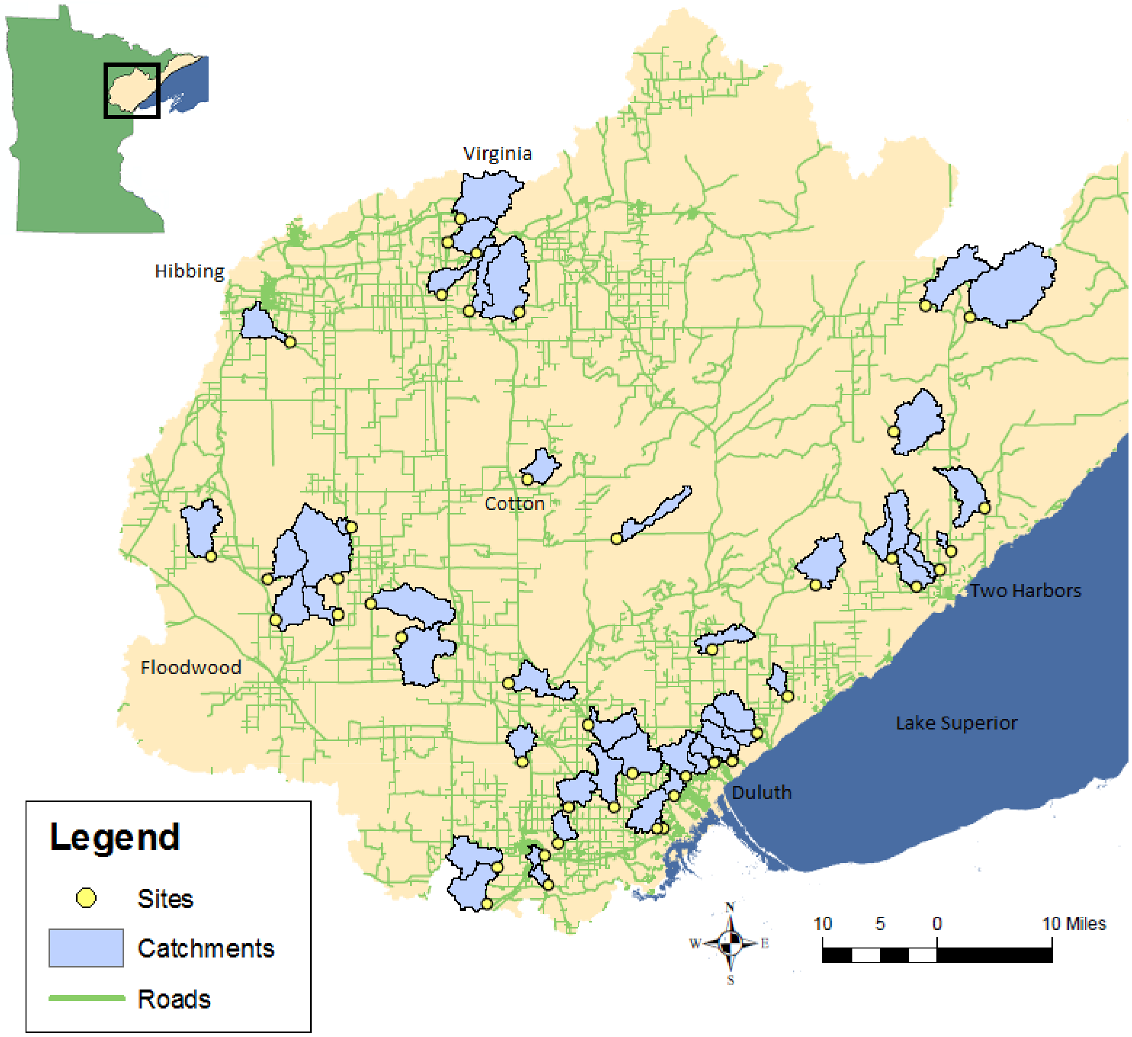

Virginia
Hibbing
Cotton
Two Harbors
Floodwood
Lake Superior
Duluth
Legend
Sites
Catchments
Roads
N
W
E
S
10
5
0
10 Miles

FIGURE 3.

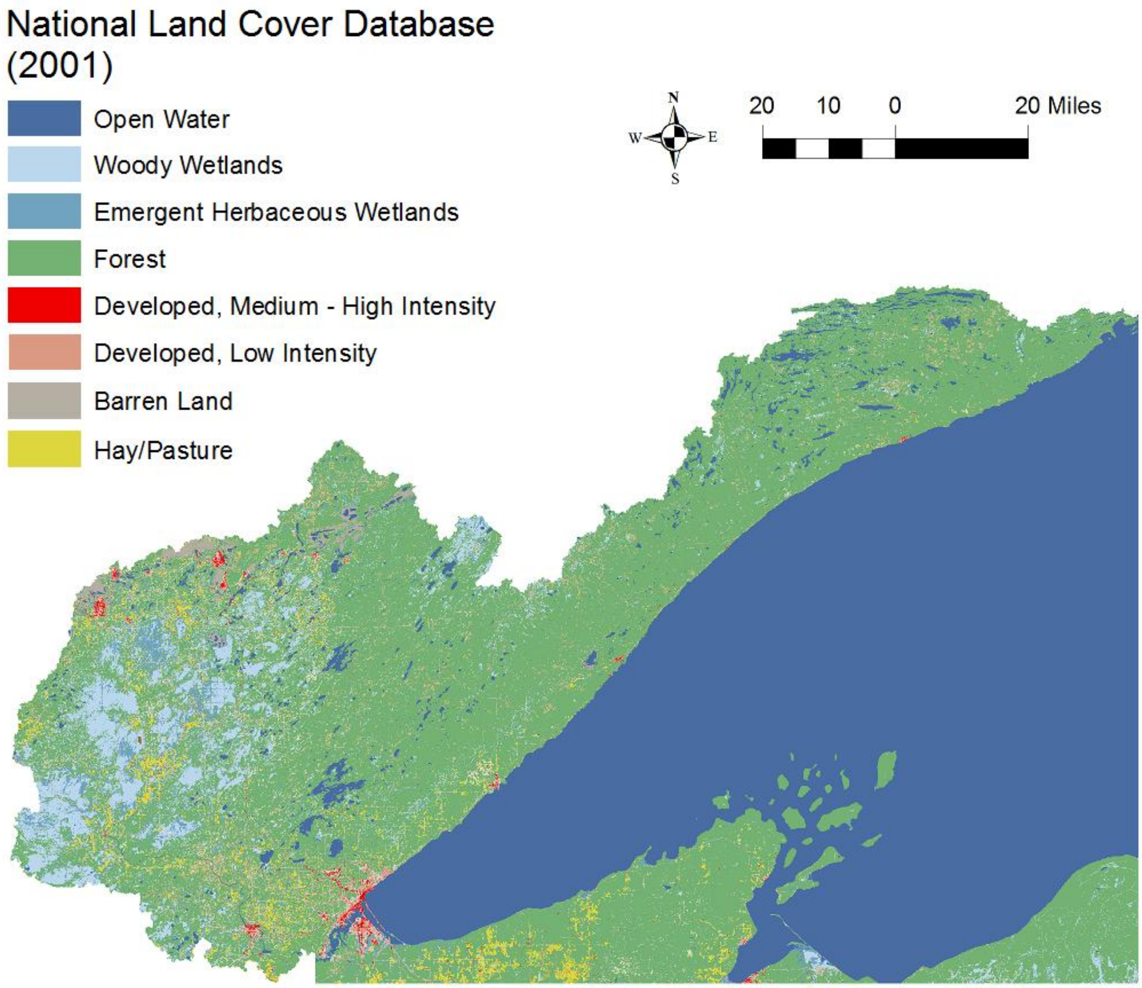

National Land Cover Database
(2001)
Open Water
Woody Wetlands
Emergent Herbaceous Wetlands
Forest
Developed, Medium - High Intensity
Developed, Low Intensity
Barren Land
Hay/Pasture
N
W
E
S
20
10
0
20 Miles

FIGURE 4.

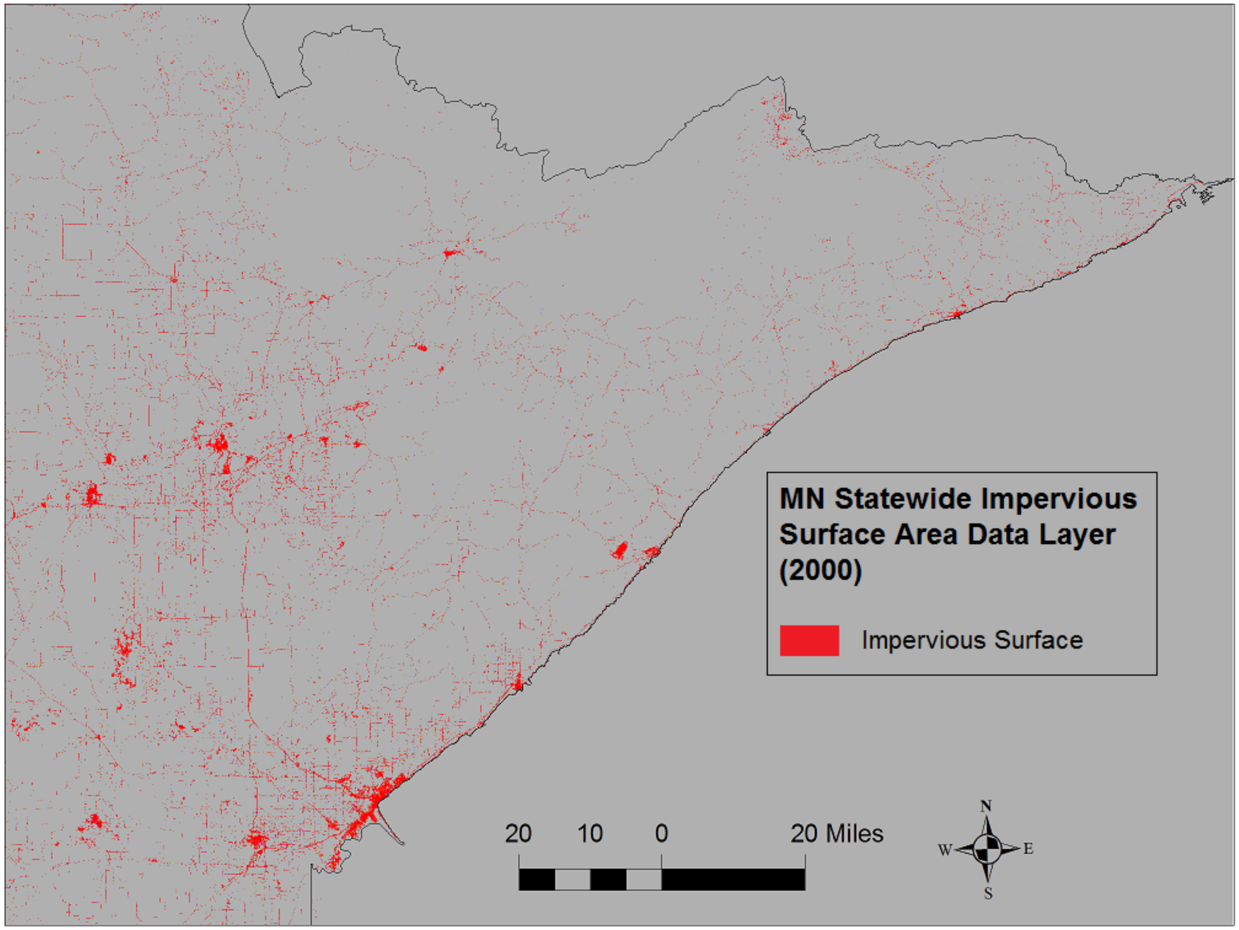

MN Statewide Impervious Surface Area Data Layer (2000)
Impervious Surface
20 10 0 20 Miles
N
W
E
S

FIGURE 5.

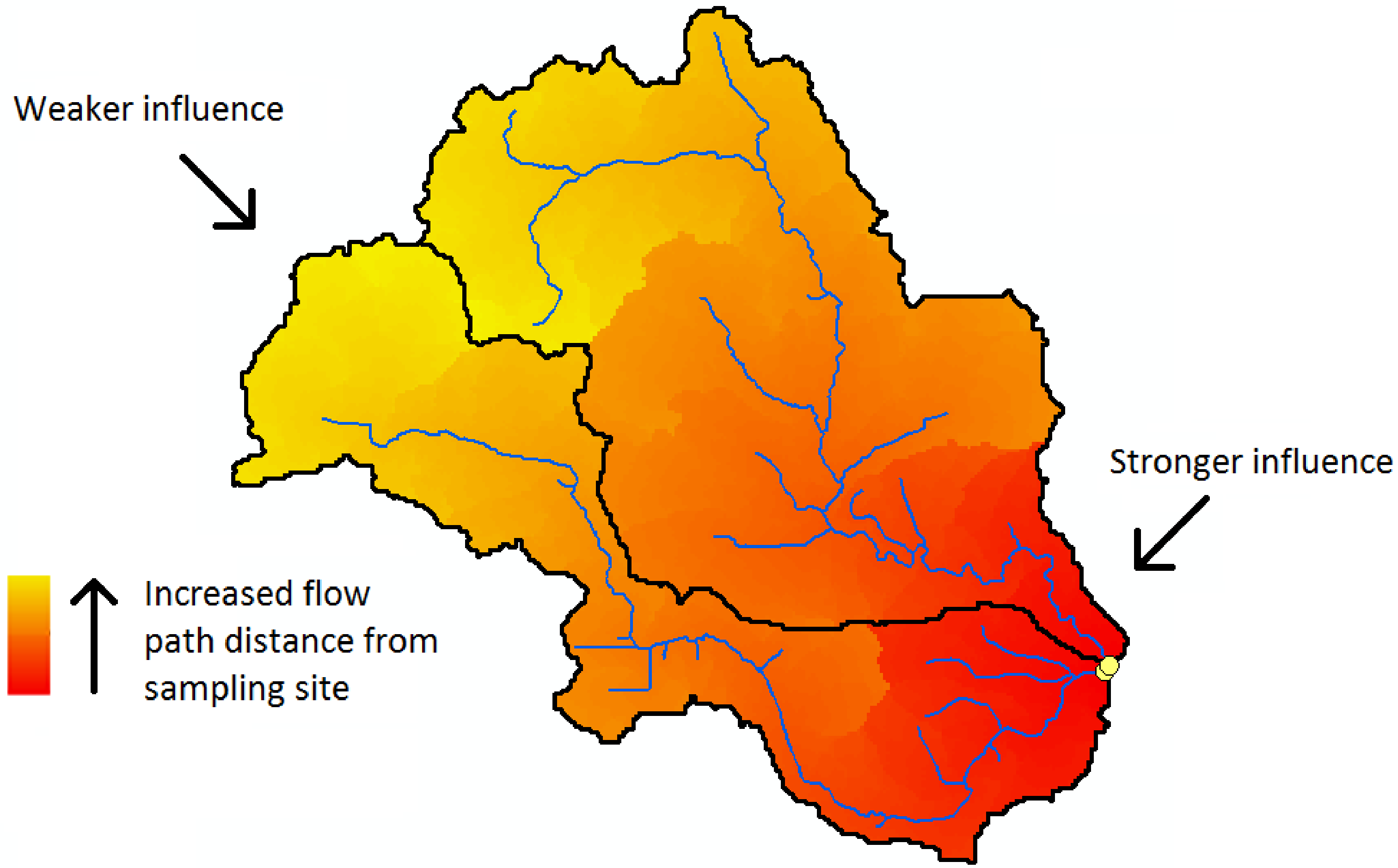

Weaker influence
Stronger influence
Increased flow
path distance from
sampling site

FIGURE 6.

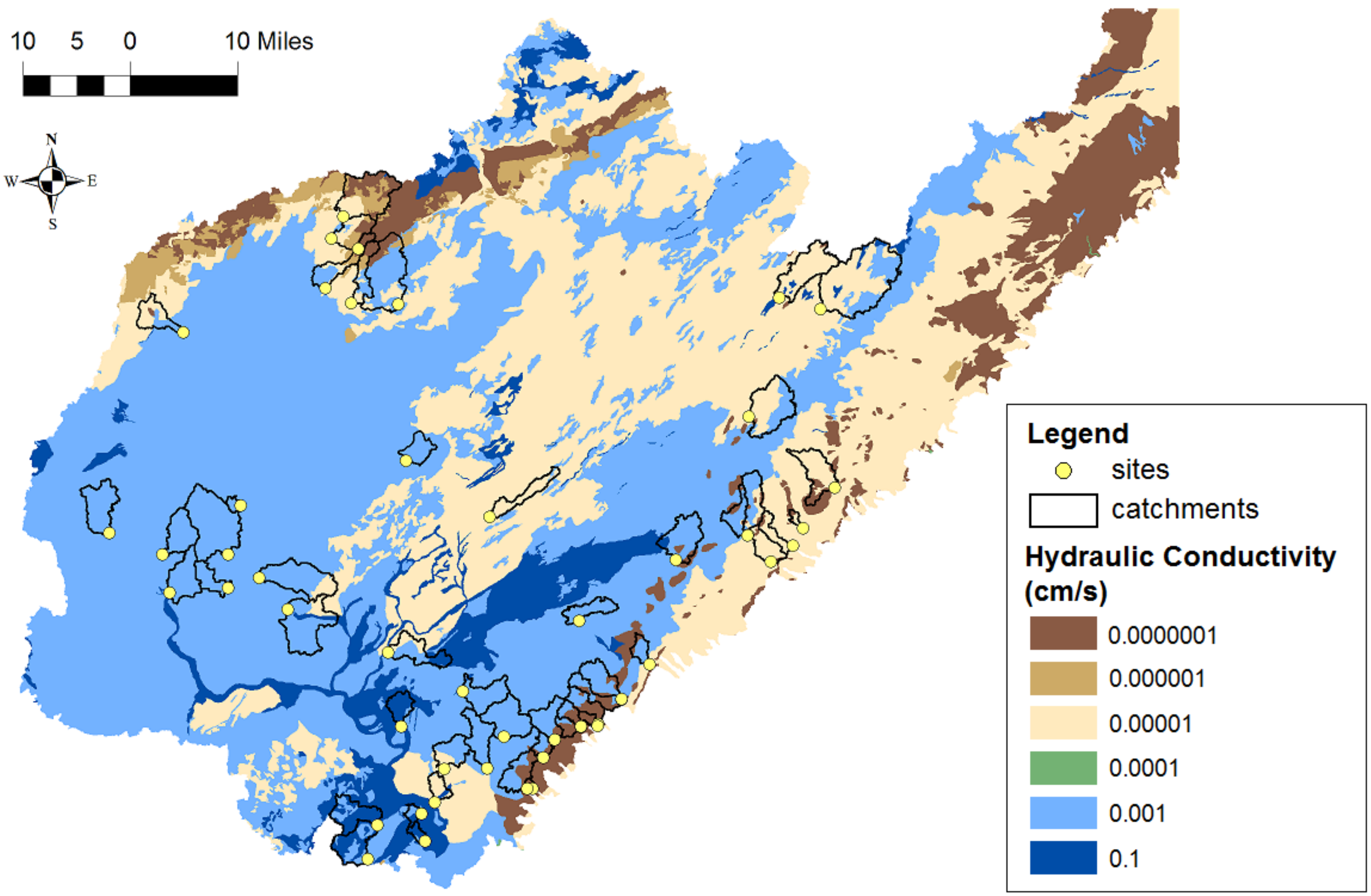

10 5 0 10 Miles
N
W
E
S
Legend
sites
catchments
Hydraulic Conductivity (cm/s)
0.0000001
0.000001
0.00001
0.0001
0.001
0.1

FIGURE 7.

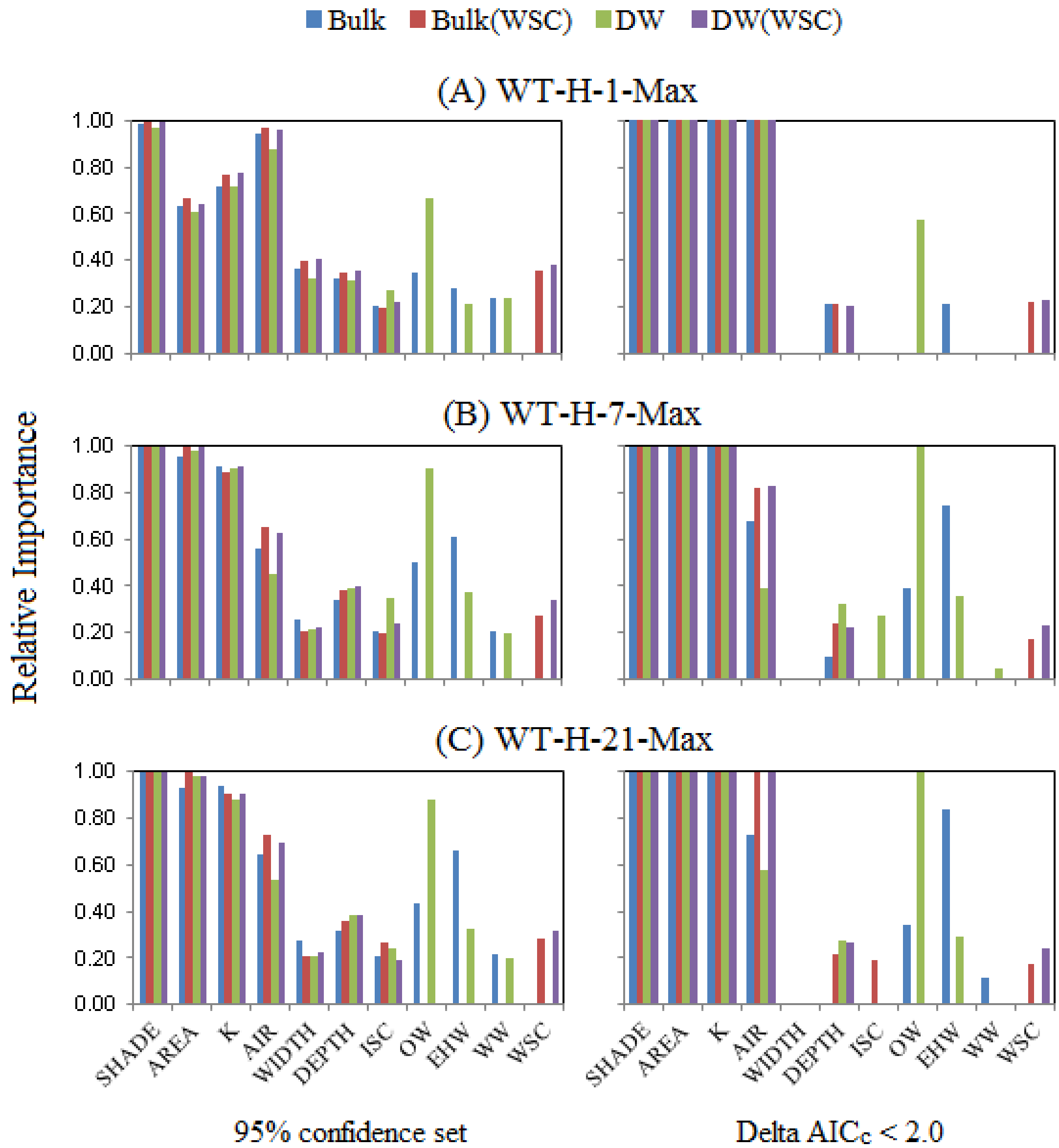

Bulk
Bulk(WSC)
DW
DW(WSC)
(A) WT-H-1-Max
(B) WT-H-7-Max
(C) WT-H-21-Max
Relative Importance
1.00
0.80
0.60
0.40
0.20
0.00
SHADE
AREA
K
AIR
WIDTH
DEPTH
ISC
OW
EHW
WW
WSC
95% confidence set
Delta AICc < 2.0

FIGURE 8.

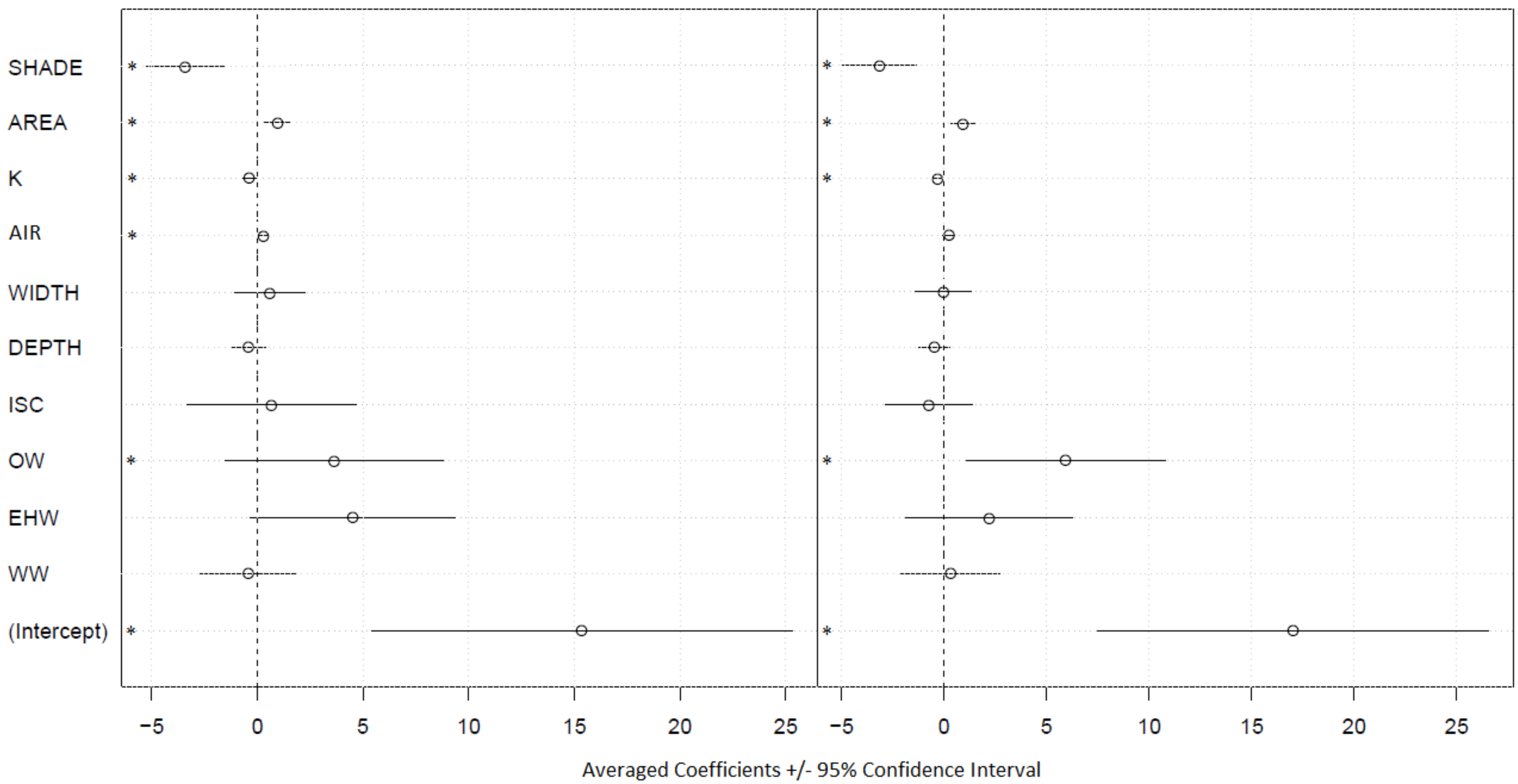
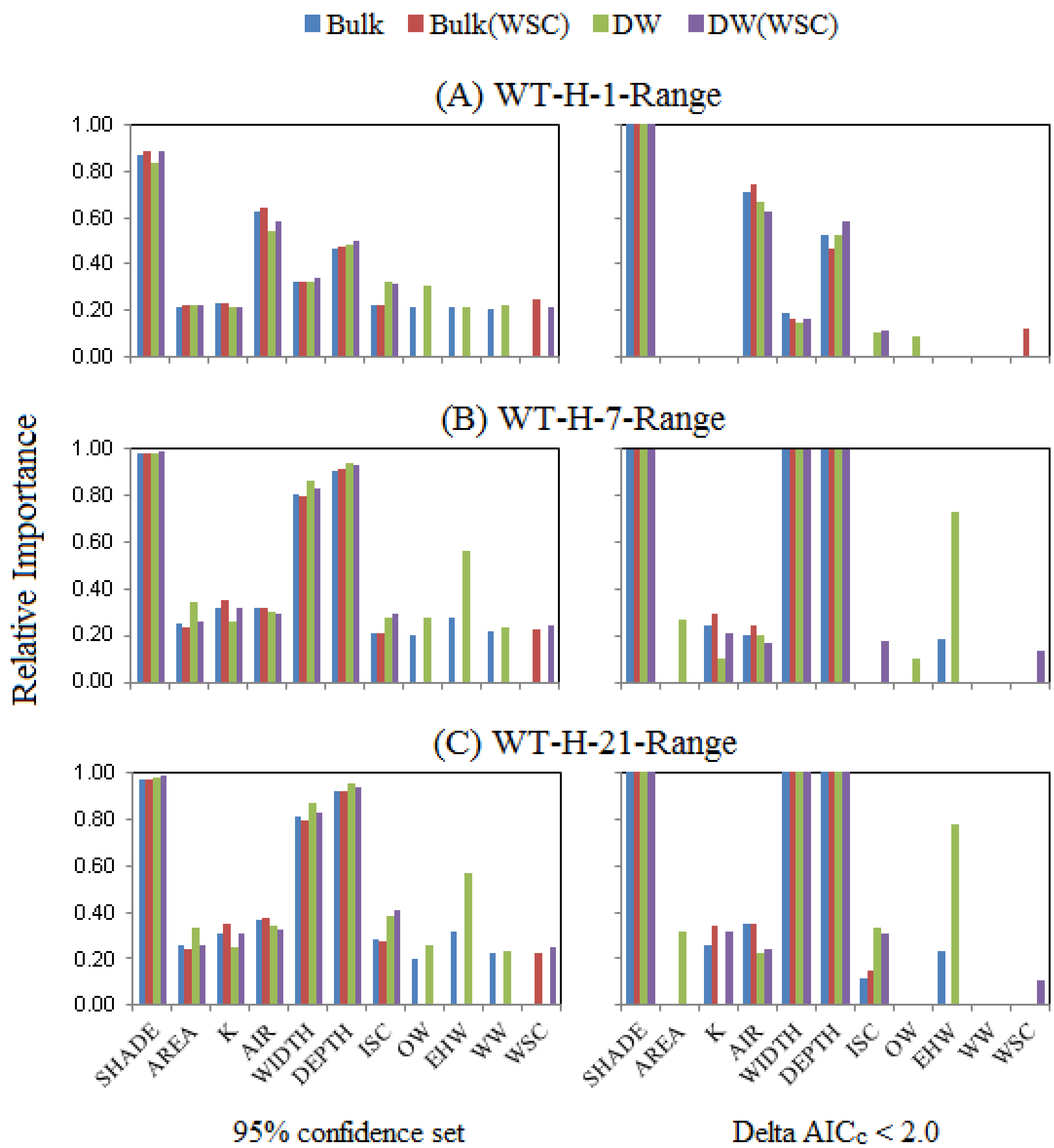

SHADE
AREA
K
AIR
WIDTH
DEPTH
ISC
OW
EHW
WW
(Intercept)
−5 0 5 10 15 20 25
−5 0 5 10 15 20 25
Averaged Coefficients +/- 95% Confidence Interval

FIGURE 9.



Bulk
Bulk(WSC)
DW
DW(WSC)
(A) WT-H-1-Range
(B) WT-H-7-Range
(C) WT-H-21-Range
Relative Importance
1.00
0.80
0.60
0.40
0.20
0.00
SHADE
AREA
K
AIR
WIDTH
DEPTH
ISC
OW
EHW
WW
WSC
95% confidence set
Delta AICc < 2.0

FIGURE 10.

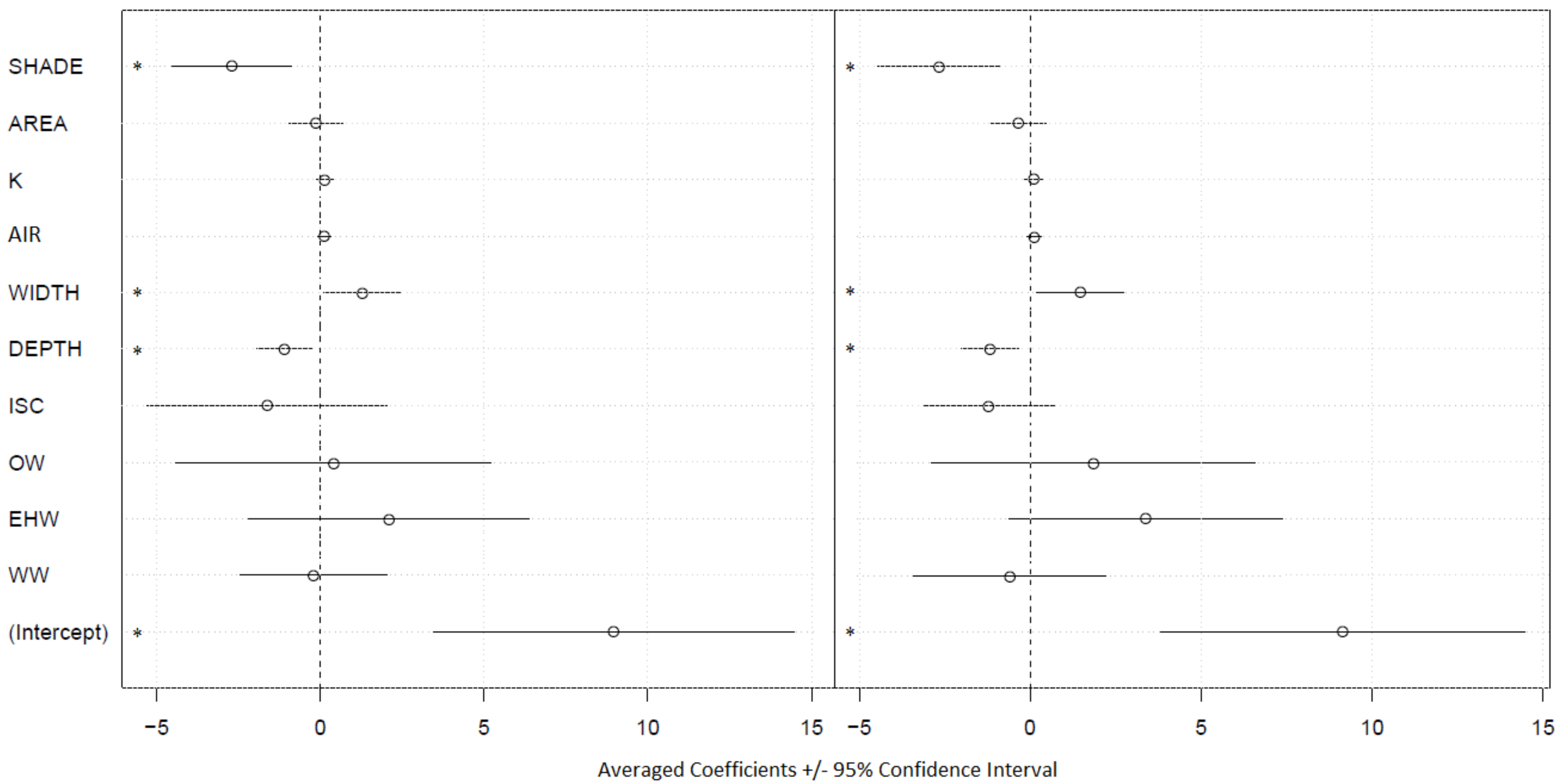
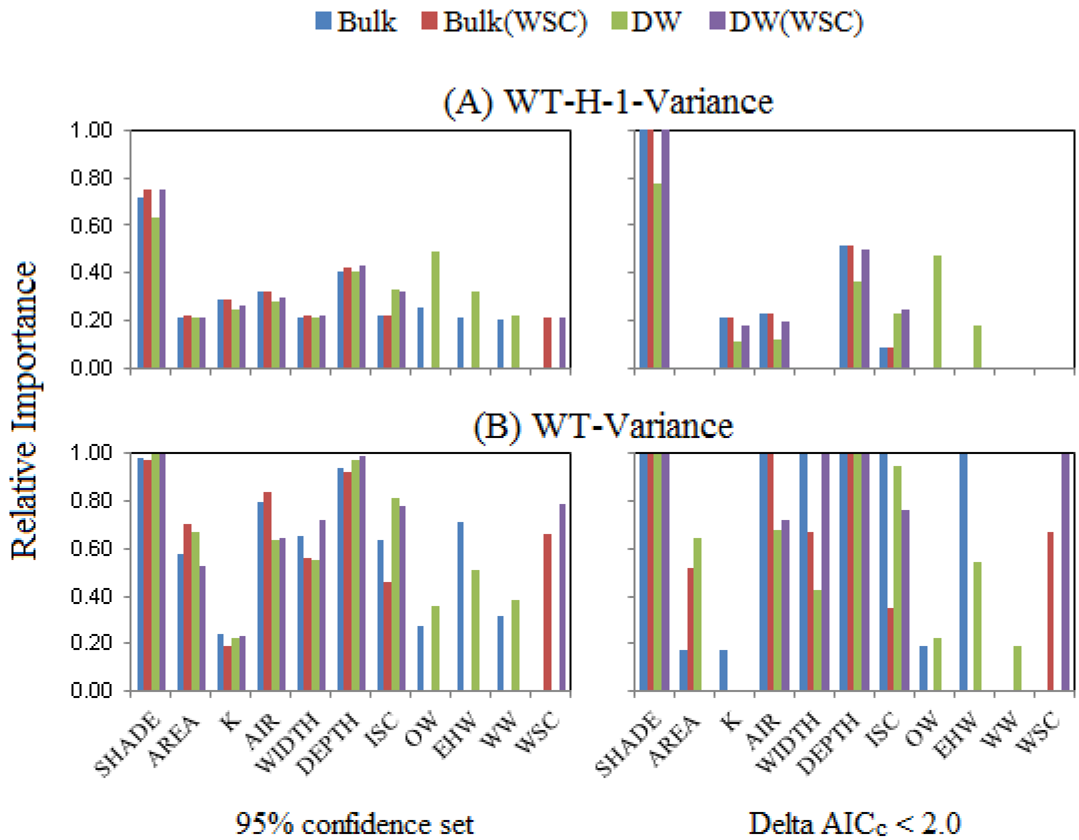

SHADE
AREA
K
AIR
WIDTH
DEPTH
ISC
OW
EHW
WW
(Intercept)
−5
0
5
10
15
Averaged Coefficients +/- 95% Confidence Interval

FIGURE 11.



Bulk
Bulk(WSC)
DW
DW(WSC)
(A) WT-H-1-Variance
(B) WT-Variance
Relative Importance
1.00
0.80
0.60
0.40
0.20
0.00
SHADE
AREA
K
AIR
WIDTH
DEPTH
ISC
OW
EHW
WW
WSC
95% confidence set
Delta AICc < 2.0

FIGURE 12.

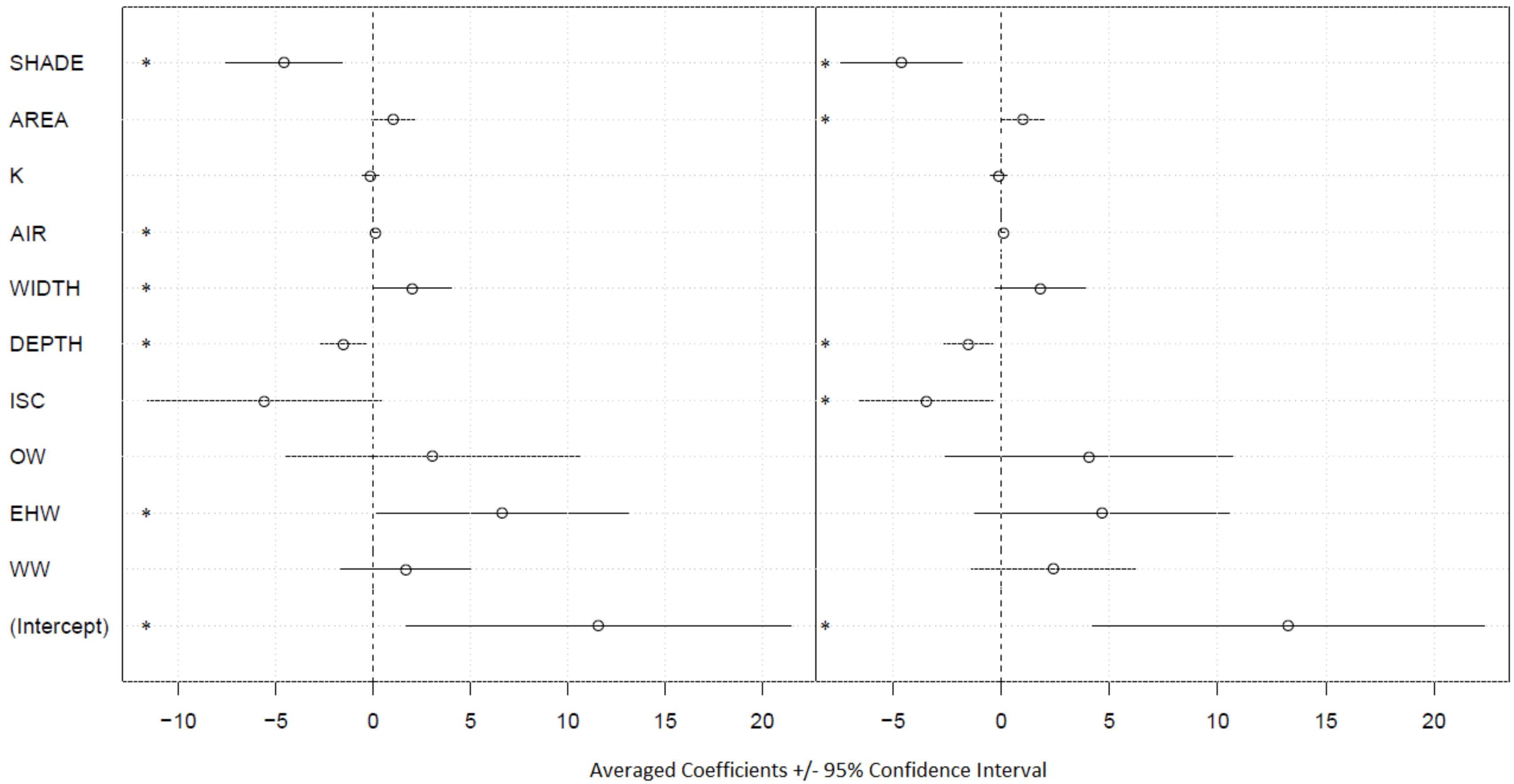
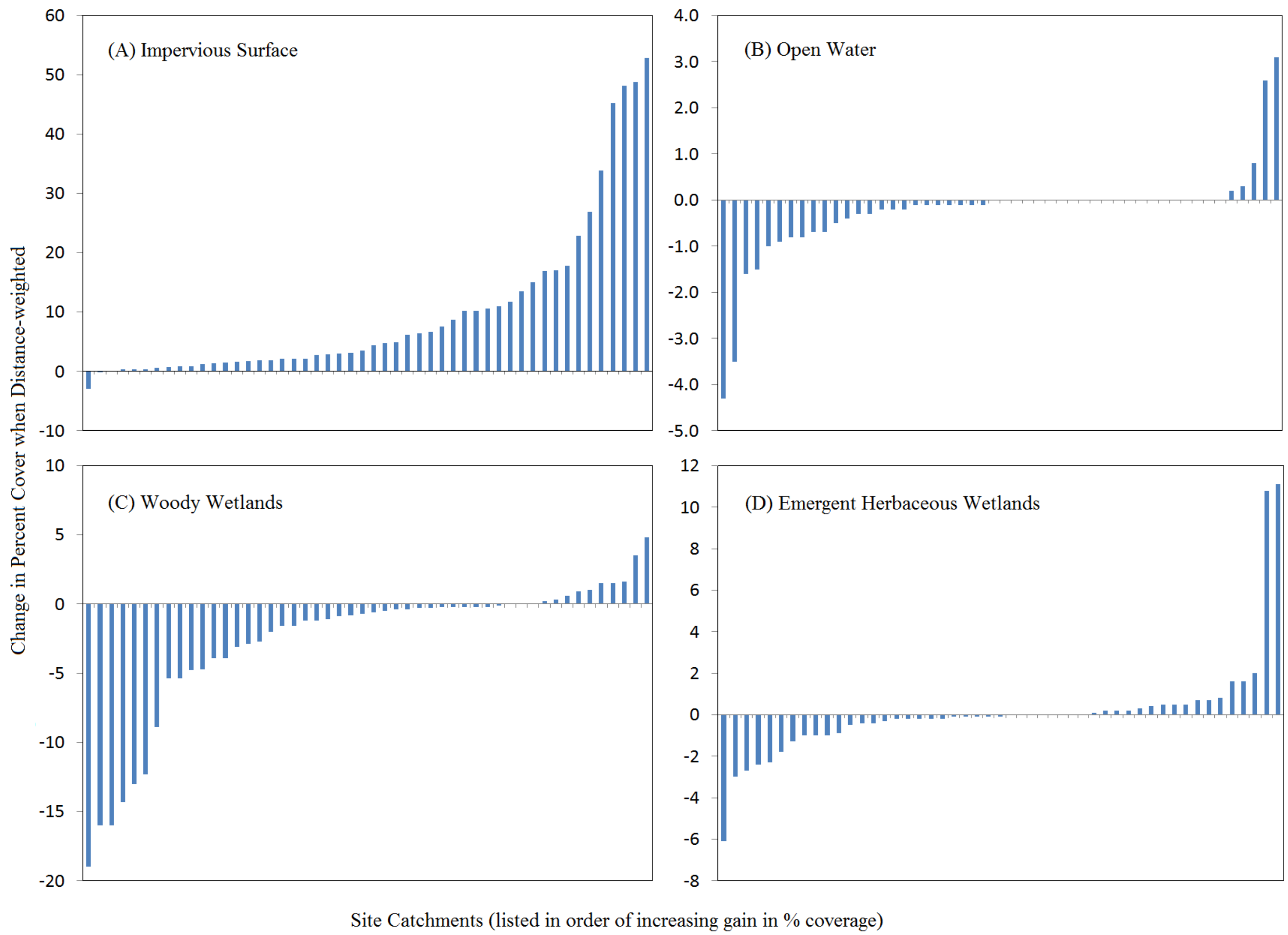
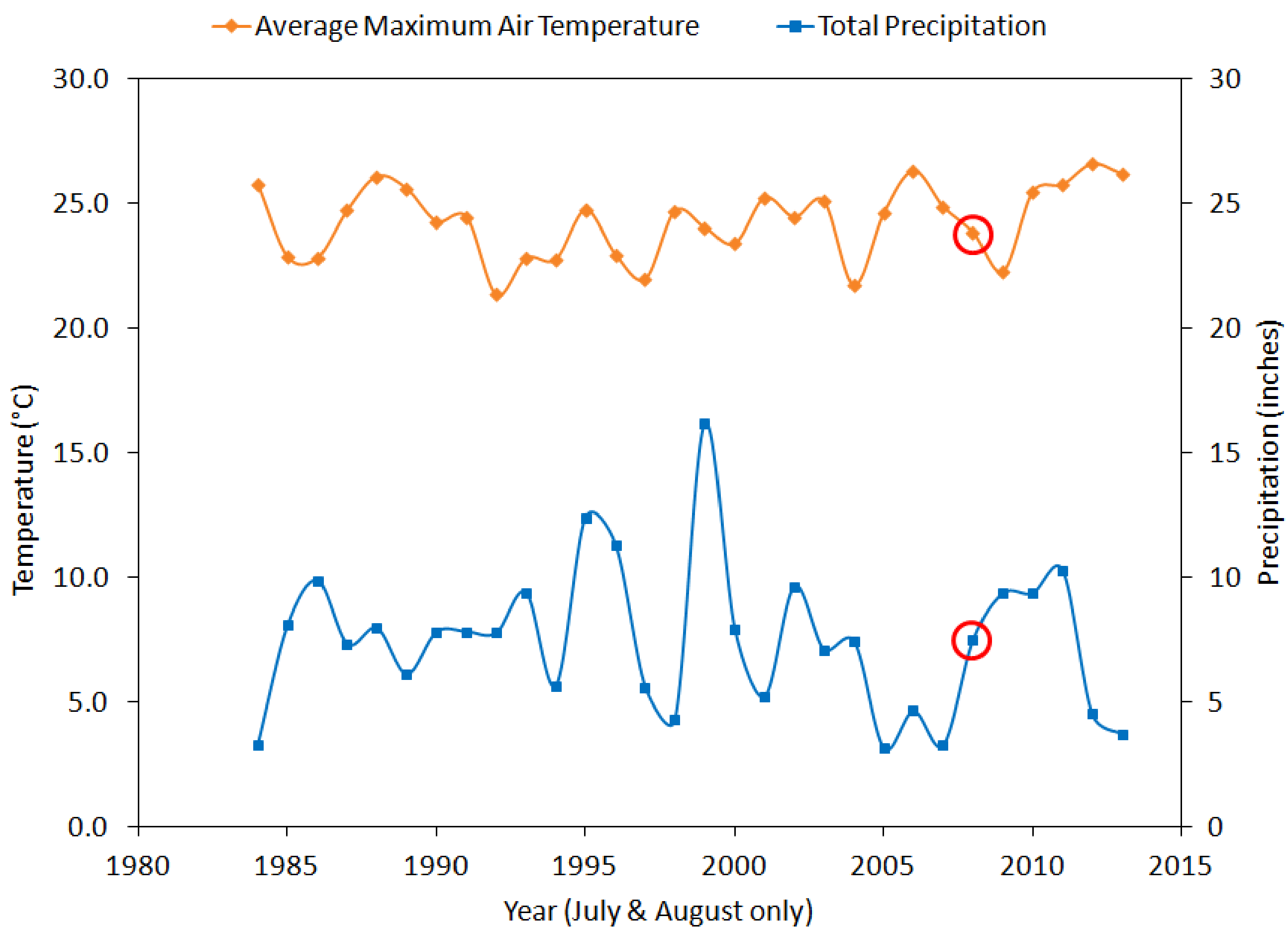

SHADE
AREA
K
AIR
WIDTH
DEPTH
ISC
OW
EHW
WW
(Intercept)
−10
−5
0
5
10
15
20
−5
0
5
10
15
20
Averaged Coefficients +/- 95% Confidence Interval

FIGURE 13.



(A) Impervious Surface
(B) Open Water
(C) Woody Wetlands
(D) Emergent Herbaceous Wetlands
Change in Percent Cover when Distance-weighted
Site Catchments (listed in order of increasing gain in % coverage)

FIGURE 14.



Average Maximum Air Temperature
Total Precipitation
Temperature (°C)
Precipitation (inches)
Year (July & August only)
30.0
25.0
20.0
15.0
10.0
5.0
0.0
30
25
20
15
10
5
0
1980
1985
1990
1995
2000
2005
2010
2015

FIGURE 15.

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Appendix A. Supplementary Tables

TABLE A.1.—List of land cover variables summarized from the National Land Cover Database (2001) and the MN Statewide Impervious Surface Area data set (2000). All variables are calculated as percent coverage.

Abbreviation	Variable description
OW	Open water
OW100	Open water within riparian buffer of 100 meters
OW200	Open water within riparian buffer of 200 meters
OW500	Open water within riparian buffer of 500 meters
OW1000	Open water within riparian buffer of 1000 meters
OW2000	Open water within riparian buffer of 2000 meters
OW5000	Open water within riparian buffer of 5000 meters
OWCON	Open water connected to the stream
OWDW	Open water distance-weighted
EHW	Emergent herbaceous wetlands
EHW100	Emergent herbaceous wetlands within riparian buffer of 100 meters
EHW200	Emergent herbaceous wetlands within riparian buffer of 200 meters
EHW500	Emergent herbaceous wetlands within riparian buffer of 500 meters
EHW1000	Emergent herbaceous wetlands within riparian buffer of 1000 meters
EHW2000	Emergent herbaceous wetlands within riparian buffer of 2000 meters
EHW5000	Emergent herbaceous wetlands within riparian buffer of 5000 meters
EHWCON	Emergent herbaceous wetlands connected to the stream
EHWDW	Emergent herbaceous wetlands distance-weighted
WW	Woody wetlands
WW100	Woody wetlands within riparian buffer of 100 meters
WW200	Woody wetlands within riparian buffer of 200 meters
WW500	Woody wetlands within riparian buffer of 500 meters
WW1000	Woody wetlands within riparian buffer of 1000 meters
WW2000	Woody wetlands within riparian buffer of 2000 meters
WW5000	Woody wetlands within riparian buffer of 5000 meters
WWCON	Woody wetlands connected to the stream
WWDW	Woody wetlands distance weighted
WSC	Water storage capacity (sum of OW + WW + EHW)
WSCCON	Water storage capacity connected to the stream
WSCDW	Water storage capacity distance-weighted

TABLE A.1.—(continued)

Abbreviation	Variable description
ISC	Impervious surface cover
ISC100	Impervious surface cover within riparian buffer of 100 meters
ISC200	Impervious surface cover within riparian buffer of 200 meters
ISC500	Impervious surface cover within riparian buffer of 500 meters
ISC1000	Impervious surface cover within riparian buffer of 100 meters
ISC2000	Impervious surface cover within riparian buffer of 2000 meters
ISC5000	Impervious surface cover within riparian buffer of 5000 meters
ISCCON	Impervious surface cover connected to the stream
ISCDW	Impervious surface cover distance weighted

TABLE A.2.—Data collected at each site.

Characteristic	Method of Assessment
Measured continuously	
Air temperature (°C)	Recorded at 30 minute intervals
Water temperature (°C)	Recorded at 5 minute intervals
Measured once at each site	
Electrical conductance (umhos @ 25°C)	Field measurement using YSI multimeter
Dissolved oxygen (% ; mg/L)	Field measurement using YSI multimeter
pH	Field measurement using YSI multimeter
Turbidity (ntu)	Sample taken to lab for analysis with turbidimeter (HACH 2100 calibrated with formazin factory sealed calibration standards)
Transparency (m)	Visual estimation using 120cm transparency tube
Stream discharge (m^3)	Midsection method using current meter
Catchment area (km^2)	Computer estimation from ArcHydro output of land area draining to temperature logger
Catchment land cover (%)	Percentage of catchment area calculated for each land use classification based on 2001 NLCD layer in ArcGIS
Hydraulic conductivity (cm/s)	Computer estimation based on surficial geology layer in ArcGIS
Measured at each transect	
Channel type	Categorized as riffle, run, or pool
Riparian land cover (near)	Visual estimation of dominant land cover type 0-30m perpendicular to stream
Riparian land cover (far)	Visual estimation of dominant land cover type 30-100m perpendicular to stream
Fish habitat (%)	Visual estimation to nearest 5% of the following: undercut bank, overhanging vegetation, woody debris, boulder, submergent vegetation, emergent vegetation, and other
Shade (%)	Estimation using a spherical densiometer; average of 6 readings: right bank, left bank, center-upstream, center-downstream, center-left bank, and center-right bank
Width (m)	Average stream width at wetted perimeter from ten transects
Measured at four equidistant points and the thalweg within each transect	
Depth (m)	Average depth at five points along ten transects
Substrate (%)	Visual estimation to nearest 5% of each substrate type
Depth of fine sediments (m)	Refusal depth measured with a one inch diameter wading rod
Embeddedness of coarse substrates (%)	Visual estimation to nearest 25%

TABLE A.3.—Catchment and reach characteristics listed for each of the 50 streams sampled in this study. Reach characteristics were measured during the period of July-August 2008. Land cover was summarized from digital layers created in 2000 and 2001.

Stream	Catchment area (km^2)	Mean width (m)	Mean depth (m)	Shade (%)	Forest (%)	Impervious surfaces (%)	Open water (%)	Woody wetlands (%)	Emergent herbaceous wetlands (%)	Hydraulic conductivity (cm/s)
Amity Creek	14.2	3.3	0.11	92	78	2.9	0.9	0.3	0.1	1.58E-06
Amity Creek, East Branch	21.0	3.5	0.13	74	82	2.2	0.2	0.6	0.7	8.00E-04
Big Sucker Creek	30.0	4.0	0.61	59	95	0.1	0.7	1.0	0.8	1.00E-03
Chalberg Creek	23.2	2.9	0.23	50	74	1.3	1.5	6.8	2.5	1.00E-03
Chester Creek	6.8	2.3	0.14	89	52	12.1	0.2	0.1	0.3	1.39E-06
Chester Creek, East Branch	8.1	2.6	0.12	93	80	1.9	0.4	0.0	0.1	1.57E-06
Cloquet River	91.4	7.7	0.22	42	74	0.1	1.4	15.9	0.4	2.18E-04
Crystal Creek	9.3	3.3	0.36	93	36	3.6	0.0	1.9	4.1	5.00E-05
East Two River	46.8	3.8	0.55	61	45	10.9	6.2	0.3	2.5	1.17E-06
Elbow Creek (Eveleth)	3.8	1.4	0.14	70	52	19.9	1.0	0.4	0.3	2.21E-08
Elbow Creek (Iron Jct.)	20.3	3.6	0.24	32	55	4.8	6.6	2.0	1.2	1.00E-05
Ely Creek	54.0	3.0	0.15	74	49	3.1	11.8	18.4	1.7	1.00E-04
Encampment River	27.9	4.2	0.18	73	88	0.4	0.3	3.2	2.9	1.00E-05
Hay Creek	18.2	4.2	0.21	94	59	1.5	0.1	2.5	4.2	4.54E-05
Johnson Creek	12.9	1.6	0.32	37	52	2.8	0.3	1.9	7.3	8.00E-02
Joula Creek	23.3	1.8	0.20	81	39	0.3	0.2	48.3	5.8	1.00E-03
Keene Creek	7.4	2.6	0.18	90	66	4.1	0.0	0.9	0.3	1.55E-06
Kingsbury Creek	20.8	4.3	0.23	88	60	7.9	0.2	3.7	1.4	1.55E-06
Knife River	21.5	4.3	0.46	81	94	0.8	0.1	0.7	0.3	1.00E-05
Lester River	15.4	2.3	0.18	64	80	1.8	2.3	2.4	1.5	1.00E-03
Little Knife River	16.0	3.7	0.59	36	73	1.9	0.1	2.4	0.3	8.00E-06
Little Otter Creek	26.8	3.1	0.48	61	65	1.5	0.1	13.3	3.4	1.00E-02

TABLE A.3.—(continued)

Stream	Catchment area (km^2)	Mean width (m)	Mean depth (m)	Shade (%)	Forest (%)	Impervious surfaces (%)	Open water (%)	Woody wetlands (%)	Emergent herbaceous wetlands (%)	Hydraulic conductivity (cm/s)
Little Stewart River	10.5	4.4	0.32	77	67	2.4	0.0	6.0	0.0	1.00E-05
Long Lake Creek	17.0	2.0	0.15	58	55	6.8	8.4	2.8	1.4	1.00E-04
McCarthy Creek	13.9	3.5	0.26	77	95	0.1	0.2	1.1	1.0	8.00E-04
Miller Creek	19.0	3.4	0.32	53	47	20.6	0.2	0.3	1.8	5.00E-04
Murphy Creek	37.1	5.4	0.51	57	86	0.3	0.7	8.6	0.1	1.00E-05
Muskrat Creek	45.5	3.9	0.32	37	52	2.2	1.4	28.3	13.3	1.00E-03
Otter Creek	40.8	2.1	0.17	27	54	0.7	2.4	30.4	7.4	8.00E-04
Otter Creek (Cartwright Rd.)	24.9	3.6	0.38	16	69	1.3	0.2	12.8	7.1	4.30E-03
Pine Creek	41.8	6.9	0.38	54	90	0.2	1.5	4.0	0.4	1.00E-04
Rocky Run Creek (St. Louis River Rd.)	22.5	5.2	0.37	91	58	2.1	0.1	0.6	2.4	1.00E-03
Rocky Run Creek (Maple Grove Rd.)	31.4	5.3	0.70	28	67	3.9	0.1	0.5	1.1	1.00E-03
Skunk Creek	61.0	1.3	0.06	97	15	6.0	0.0	41.6	28.8	1.00E-03
Talmadge River	7.9	2.4	0.14	85	77	1.1	0.1	14.4	0.6	1.00E-05
Tischer Creek	14.1	4.0	0.16	97	55	10.3	0.3	0.5	0.0	1.56E-06
Trib. to East Swan River (Koivu Rd.)	19.4	3.0	0.43	29	52	3.8	0.3	2.0	2.4	9.71E-07
Trib. to East Two River (CR 7)	19.9	3.8	0.31	21	35	10.1	5.5	1.6	6.5	6.39E-07
Trib. to Floodwood River (Hwy 73)	25.6	1.6	0.21	59	33	0.8	0.0	49.3	13.0	1.00E-03
Trib. to Floodwood River (Wawina Rd.)	29.1	5.0	1.01	35	72	0.1	0.6	15.2	4.4	1.00E-03
Trib. to Kingsbury Creek	1.4	2.1	0.07	90	28	19.8	0.0	1.1	0.0	1.00E-08
Trib. to St. Louis River (Creek Rd.)	13.4	1.7	0.26	88	10	1.7	0.1	78.0	8.1	1.00E-03

TABLE A.3.—(continued)

Stream	Catchment area (km^2)	Mean width (m)	Mean depth (m)	Shade (%)	Forest (%)	Impervious surfaces (%)	Open water (%)	Woody wetlands (%)	Emergent herbaceous wetlands (%)	Hydraulic conductivity (cm/s)
Trib. to St. Louis River (Hwy 61)	4.9	1.4	0.12	58	25	26.1	0.0	3.9	3.2	1.00E-01
Trib. to St. Louis River (Pirtalla Rd.)	3.6	1.4	0.20	93	15	7.4	0.0	48.3	11.8	1.00E-03
Trib. to Stewart River	2.7	1.5	0.12	94	91	0.9	0.0	3.5	0.0	1.46E-07
Trib. to Thompson Reservoir	4.9	3.4	0.40	93	64	11.3	1.1	2.1	7.6	8.00E-02
Trib. to Tischer Creek	4.0	1.3	0.10	82	72	8.6	0.0	1.3	0.0	1.00E-08
Trib. to Whiteface River	14.6	1.6	0.85	32	61	0.3	0.3	32.4	2.8	1.00E-03
Us-Kab-Wan-Ka River	17.1	4.5	0.99	53	79	0.1	6.0	1.3	0.2	2.01E-05
White Pine River	22.7	3.7	0.50	54	65	5.4	9.3	1.5	0.9	1.00E-03

Appendix B. Stream Temperature Modeling

Stream temperature modeling has two basic approaches: (1) a statistical approach using empirical data to identify correlations between predictor and response variables; or (2) a mechanistic approach, which uses heat flux equations to provide realistic predictions of cause and effect. There are advantages and disadvantages to both approaches. An obvious advantage of the mechanistic modeling approach is its application of fundamental concepts of heat transport. Input parameters describe energy flow through systems based on the physical properties of the system. Gaffield et al. (2005) used a heat transport equation to develop a model that predicts mean stream temperature during the warmest seven consecutive days of summer. They evaluated their model using four streams in Southwestern Wisconsin, and observed accuracy within 1°C. Similar techniques were employed by Norton and Bradford (2009) with equally impressive results. Other researchers have used a mechanistic approach to model the effects of land use (LeBlanc et al. 1997) and climate change (Gooseff et al. 2005) on water temperature. All of these studies benefit by requiring data from a relatively small number of streams; however, they are also at a disadvantage because their predictive capabilities are somewhat limited to a specific study area (Hill et al. 2013). Gaffield et al. (2005) suggest these models could be applied to similar streams outside of the intended study area with adjustment of the input parameters, but additional time and data would still be required. Another benefit of mechanistic models is that they are deterministic by nature. In other words, these models inherently provide insight into cause and effect relationships, which aids in the evaluation of various management strategies (LeBlanc et al. 1997; Gaffield et al. 2005; Norton and Bradford 2009).

Statistical models, on the other hand, lend themselves to research with large empirical data sets with the goal of finding the most influential predictor variables for a given response (Wehrly et al. 2006; Isaak et al. 2010; Lyons et al. 2010). The statistical approach commonly uses either stochastic or regression techniques to identify correlations among variables (Caissie 2006), often at a much larger geographic scale (Mohseni and Stefan 1999; Wehrly et al. 2006). Although not always the case, stochastic and regression models frequently include fewer input parameters, which can make them easier to use than mechanistic models (Caissie et al. 2001). The disadvantages are that large empirical data sets can be costly to obtain, results more often indicate correlation than causation, and the model predictions are limited to the conditions encompassed by the data set. Still, both modeling approaches have provided useful information regarding stream temperature relationships (Krause et al. 2004; Caissie 2006).